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# PRIVATE SUPPLEMENTAL INSURANCE AND MENTAL HEALTH CARE UTILIZATION IN CANADA - AN INVESTIGATION USING NONPARAMETRIC ESTIMATION METHODS


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# Private Supplemental Insurance and Mental Health Care Utilization in Canada - An Investigation Using Nonparametric Estimation Methods

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The heterogeneous nature of mental illness leads to individual treatment plans that may consist of community-based non-physician mental health services (e.g. psychologists and social workers) and prescription medications. While Canada's universal system of public health insurance fully covers the cost of medically necessary hospital and physician services, the public plan generally does not cover the use of prescription drugs. The purpose of this paper is to investigate the role of supplementary insurance plans in the utilization of prescription drugs for mental illness and mental health service providers. I employ nonparametric conditional probability density function estimation methods and nonparametric regression estimation methods. I find that supplemental insurance affects the utilization of medication. Furthermore, I find that conditional on having used a mental health pharmaceutical, those with insurance are more likely to use a higher number medications than those without insurance. My results show that lack of private supplemental insurance may act as a barrier for some individuals to access important mental health goods and services.

## Introduction

Mental illness is a broad term used to encompass all psychological disorders. Individuals who suffer from mental illness may suffer from one or multiple disorders in varying degrees of severity. Treatment, therefore, must be tailored to the individual patient and may include a combination of physician, community-based non-physician health services (e.g. psychologists and social workers) and prescription medications. In Canada, the public health care system covers medically necessary physician and in-hospital services, however, there

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is no universal coverage for community-based non-physician services or prescription drugs for mental illness (Hurley and Mulvale 2008). Some provinces have enacted public pharmacare programs but these programs are restricted to seniors and individuals receiving some other form of government assistance. Approximately twenty-six percent of those with prescription drug coverage receive it through public programs (Statistics Canada 2014).

Private insurers offer policies that supplement the public system to cover prescription drugs and non-physician services. Approximately sixty-one percent of Canadians receive private supplemental insurance through their employer, seven percent purchase this coverage out-of-pocket (i.e. pay premiums themselves), and six percent hold a combination of the two (individuals topping up their employer provided coverage) (Statistics Canada 2014). With approximately three quarters of supplemental insurance holders receiving coverage through work or by paying premiums themselves, the distribution of insurance holders tends to be skewed to higher-income, employed Canadians. If these individuals gain access to services otherwise unavailable without insurance, the distribution of mental health care would be inequitable.

Mulvale and Hurley (2008) looked at the impact of private supplemental insurance on the use of mental health pharmaceuticals and health care professionals for mental health issues. They found that insurance had a positive effect on the probability of using antipsychotics and mood-stabilizers but had no effect on provider usage. Using a logit specification, they found little evidence of endogeneity of private insurance. Unfortunately, the authors were only able to study the utilization of prescription drugs by a binary use/no use measure and were unable to study the effect of insurance on the intensity of use. Devlin et al. (2011) studied the effect of prescription drug insurance on the use of physician services. The rationale was that those with insurance are more likely to visit health care professionals who are able to write prescriptions. The authors found that insurance positively affected the use of physician services and helped reduce hospital admissions for ambulatory care sensitive conditions.

Both studies listed above employed parametric estimation methods to study the impact of supplemental prescription drug insurance on health care utilization. Parametric estimation methods make unrealistic assumptions about the nature of the data, increasing the chances for model misspecification. When a parametric econometric model is misspecified, resulting estimates will be inconsistent rendering inferences untrustworthy. Nonparametric methods for estimating regression models and discrete choice models are well developed and provide viable alternatives to parametric methods. These nonparametric methods assume nothing about the functional form of the data generating process and are therefore free of misspecification.

The purpose of this paper is to investigate the role of supplementary insurance plans in the utilization of prescription drugs and health care professionals for mental illness using nonparametric estimation methods. I use data from the 2012 Canadian Community Health Survey - Mental Health Component (CCHS-MH), which contains information on health status, health care utilization, socioeconomic status, and an individual's social support system. My research is guided by the following questions:

1. Does a lack of insurance act as a barrier to mental health care goods and services?
2. Are individuals who have insurance more likely to take medications for mental health conditions?
3. Conditional on having taken a medication for a mental health condition, do individuals who have supplemental insurance take more medications compared to those without insurance?
4. Are individuals who have insurance more likely to visit health care professionals?
5. Conditional on having visited a health care professional for a mental health condition, do individuals who have supplemental insurance spend more time with health care providers?

I estimate the impact of insurance on four measures of mental health care utilization: binary use/no use of medications, number of medications taken (conditional on having taken a given medication), binary use/no use of health care provider for mental health issue, and number of hours spent with a mental health care provider (conditional on having visited a given provider). I find that insurance increases the probability that an individual will take an antidepressant and an antipsychotic and it affects the total number of medications taken. I also show that insurance positively affects the probability of visiting a psychiatrist and a psychologist as well as the number of hours spent with these providers. In addition, I find that a social support system and the presence of a comorbid condition plays an important role in the use of mental health care goods and services.

Following this introduction, I describe the dataset used in the analysis. In Section 3, I outline the models to be estimated and the nonparametric methods used to estimate them. Also, I include a brief overview of the methods used to select the smoothing parameters of the nonparametric estimators (analogous to model selection in parametric setting). In Section 4, I present and discuss the results for the four models. Finally, in Section 5, I conclude with a brief summary.

## Data

To estimate the relationship between private supplemental insurance and mental health care utilization, I use the 2012 CCHS-MH. The purpose of this survey is to collect information on the physical health and mental health of Canadians as well as their experiences in the health care system. The population of interest is individuals aged 15 years and older living in the ten provinces, excluding individuals in the military full-time, individuals in institutions, and individuals living on reserves or other Aboriginal settlements. After an initial selection of 43,030 dwellings, a total of 25,113 valid interviews were conducted. For the purpose of this study, I excluded any individuals who did not report a personal income, either an exact approximation or an estimated range, leaving a total of 13,050 observations.

This dataset meets the needs of this study for three reasons. Firstly, it includes four important measures of mental health care utilization. As in the 2002 Canadian Community Health Survey used in Hurley and Mulvale (2008), the survey dataset includes a binary use/no use measure of prescription drug utilization. Respondents are asked if they used a medication for mental illness in the past two days. An addition to the 2012 CCHS-MH is that data on the number of drugs used was also collected. That way, I can estimate the impact of insurance on the intensity of use. The survey also asked respondents if they visited a health care professional for a mental health issue over the past twelve months. If the respondent answered 'yes', they were then asked how many times they visited the provider and the average time spent at each visit. From there, Statistics Canada analysts derived a variable measuring the approximate number of hours spent with a given health care provider. Secondly, the dataset contains information on the respondent's insurance status. The interviewers asked whether or not the respondent had insurance that covered all or part of his or her prescription drug costs. Unfortunately, the source of the insurance (employer, public, or private) was not disclosed. Finally, as with all waves of the Canadian Community Health Survey, the dataset contains information on health status, socioeconomic status, demographics, and social support systems.

## Methods

I consider four models for estimating the effect of private supplemental insurance on mental health care utilization:

1. The effect of insurance on a binary use/no use measure of prescription drug utilization. I estimate the probability of using a given medication for a mental illness within the last two days conditional on having insurance and control variables.
2. Conditional on having taken a medication, I examine how insurance influences the number of medications taken. I estimate the conditional probability that an individual takes one, two, three, and four or more medications within a given category.
3. The impact of insurance on a binary use/no use measure of mental health care providers. I estimate the probability of using a mental health care provider for a mental illness within the last year conditional on having insurance and control variables.
4. Conditional on having visited a health care professional, I examine how insurance influences the number of hours spent with a given health care provider (controlling for health, socioeconomic status, demographic characteristics, and social supports).

The first three models described above have a discrete outcome variable. Discrete choice models are often estimated using parametric methods such as the logit or probit for a binary outcome variable or an ordered logit or ordered probit for an ordered discrete outcome variable. These methods impose strict functional form assumptions on the underlying conditional density function, increasing the risk of misspecification. A misspecified data generating process will lead to inconsistent results, rendering inferences untrustworthy. An alternative method for estimating discrete choice models is to use a nonparametric conditional probability density function (PDF) estimator, which makes no functional form assumptions and is therefore free of misspecification. For this reason, I use a nonparametric kernel conditional PDF estimator to estimate Models 1 to 3. I estimate Model 4 using the local linear estimator, a nonparametric regression estimation method.

It is also important to consider the potential endogeneity arising from unobserved characteristics correlated with insurance status that may affect utilization. The concern is that those who are unhealthy and are more likely to make use of mental health care goods and services are more likely to hold supplemental insurance. Mulvale and Hurley (2008) outlined three reasons why this analysis reduces the likelihood of this endogeneity bias. Firstly, the majority individuals who hold private supplemental insurance do not self-select this insurance but instead, obtain it through a mandatory group policy, most commonly through employment. In this case, coverage would not be linked to health status. Secondly, seniors and individuals below the poverty line receive public coverage for supplemental prescription drugs. Again, this eliminates the self-selection of insurance because of health status. Thirdly, the 2012 CCHS-MH contains many health measures. By including these measures into the model, I increase the likelihood of controlling for any unobserved heterogeneity. To test for endogeneity, I run a bivariate probit for Models 1 and 3 using the model specifications from Mulvale and Hurley (2008) and test whether insurance is endogenous. The instrument used is the marginal tax rate an individual faces. First introduced as an instrument for supplemental insurance by Stabile (2001), the marginal tax rate is correlated with holding such insurance and it has been shown that the after tax price of insurance varies across provinces (Stabile 2001). The test used is a likelihood ratio test where the null hypothesis is that there is no endogeneity present meaning that the the two probit models can be run as individual models. After running the models the p-values from these tests were above 0.1. Therefore, I ran the models under the assumption that endogeneity was not present.

## Nonparametric Conditional PDF Estimation

Nonparametric conditional density estimation begins by looking at the mathematical definition of the conditional density function. Let $Y^d$ be a discrete outcome variable such that $Y^d \in \{0,1,\ldots,c-1\}$ where $c \geq 2$ and let $X = \{X^c, X^d\}$ denote a vector of predictor variables. The superscripts $c$ and $d$ denote continuous and discrete variables in $X$, respectively. Letting $f(Y^d|X)$, $f(Y^d, X)$, and $f(X)$ denote the conditional PDF of $Y^d$ given $X$, the joint probability of $X$ and $Y$, and the marginal density of $X$, respectively, then:

$$f(Y^d|X) = \frac{f(Y^d, X)}{f(X)}.$$

Using nonparametric kernel density estimators of $f(Y^d, X)$ and $f(X)$, one can derive a direct estimator of $f(Y^d|X)$. Denote the kernel density estimators of $f(Y^d, X)$ and $f(X)$ as $\hat{f}\,(Y^d, X)$ and $\hat{f}\,(X)$, respectively. Let $X^c = [X_1^c, \ldots, X_q^c]$ and $X^d = [X_1^d, \ldots, X_r^d]$ so that there are $q$ continuous variables and $r$ discrete variables in $X$. To derive a kernel density function that incorporates both continuous and discrete variables, one can use a multivariate product kernel function. For discrete variables, I use a variation of the Aitchison and Aitken (1976) kernel function described in Li and Racine (2007). The univariate kernel function for discrete variable $X_t^d$ is given by:

$$l(X_{it}^d, X_t^d, \lambda_t) = \begin{cases} 1 & \text{if } X_{it}^d = X_t^d \\ \lambda_t & \text{otherwise} \end{cases},$$

where $0 \leq \lambda_t \leq 1$ is the smoothing parameter for $X_t^d, t = 1, \ldots, r$. The value of the univariate kernel function depends on a match between $X_{it}^d$ and $X_t^d$. A product kernel for discrete variables $X^d$ can then be written as:

$$L(X^d, X_i^d, \lambda) = \prod_{t=1}^{r} \lambda_t^{\mathbf{1}(x_{it} \neq x_t)} \quad (1)$$

where $\mathbf{1}(\cdot)$ is an index function taking a value of 1 if the logical argument in the brackets is true and 0 otherwise.

The product kernel for continuous variable $X^c$ can be written as:

$$W(X^c, h) = \prod_{s=1}^{q} \frac{1}{h_s} w\left(\frac{X_{is}^c - X_s^c}{h_s}\right), \qquad (2)$$

where $w(\cdot)$ is a univariate kernel function such as the Gaussian kernel or the Epinechnikov kernel and $h_s$ is the bandwidth for $X_s^c, s = 1, .., q$. Given a sample size of $n$ and using (1) and (2), the kernel estimator for $f(X)$ is given by:

$$\hat{f}\,(X) = n^{-1} \sum_{i=1}^{n} W\,(X^c, h) L(X^d, X_i^d, \lambda).$$

Because $Y^d$ is discrete, the kernel estimator of $f(Y^d, X)$ takes the form of:

$$\hat{f}\,(Y^d, X) = n^{-1} \sum_{i=1}^{n} \lambda_0^{\mathbf{1}(Y_i^d \neq Y^d)}\, W(X^c, h) L(X^d, X_i^d, \lambda),$$

where $\lambda_0$ is the smoothing parameter for $Y^d$. The nonparametric conditional density estimator is then given by:

$$\begin{aligned}\hat{f}\,(Y|X) &= \frac{\sum_{i=1}^{n} \lambda_0^{\mathbf{1}(Y_i^d \neq Y^d)}\, W(X^c, h) L(X^d, X_i^d, \lambda)}{\sum_{i=1}^{n} W\,(X^c, h) L(X^d, X_i^d, \lambda)} \\ &= \frac{\sum_{i=1}^{n} \lambda_0^{\mathbf{1}(Y_i^d \neq Y^d)}\, K_{\gamma,xi}}{\sum_{i=1}^{n} K_{\gamma,xi}},\end{aligned}$$

with $\gamma = (h, \lambda)$ and $K_{\gamma,xi} = W(X^c, h) L(X^d, X_i^d, \lambda)$.

## Local Linear Regression

Let $Y^c$ denote a continuous outcome variable and $X = \{X_1^c, \ldots, X_q^c, X_1^d, \ldots, X_r^d\}$ is a vector of predictor variables as above. Assume now that $Y^c$ and $X$ follow a nonparametric regression model with an additive error:

$$Y^c = g(X) + \epsilon,$$

where $g(X) = E(Y^c|X)$ is the unknown object of interest and $\epsilon$ is a vector of errors. In ordinary least squares estimation, $g(X)$ is specified as $g(X,\beta) = X\beta$, greatly simplifying the analysis. Again, restricting the data generating process to specific functional form will lead to inconsistent estimation of $g(\cdot)$ if it is incorrectly specified. Alternatively, one can use the local linear estimator to estimate $g(\cdot)$ without imposing any functional form assumptions. The local linear estimator is the $g$ that minimizes the following objective function:

$$\min_{g,\beta} \sum_{i=1}^{n} (Y_i^c - g - (X - X_i)'\beta)^2 K_{\gamma,ix}.$$

For $Y^c = (Y_1^c, \ldots, Y_n^c)'$, $A = \begin{bmatrix} 1 & (X - X_1)' \\ \vdots & \vdots \\ 1 & (X - X_n)' \end{bmatrix}$, and

$$W = diag(\prod_{s=1}^{q} \frac{1}{h_s} w\left(\frac{X_{is}^c - X_s^c}{h_s}\right) L(X^d, X_1^d, \lambda), \ldots, \prod_{s=1}^{q} \frac{1}{h_s} w\left(\frac{X_{is}^c - X_s^c}{h_s}\right) L(X^d, X_i^d, \lambda))$$

the local linear regression estimator is given by:

where $e_1$ is a $(q + r + 1) \times 1$ vector with the first entry as 1 and the rest 0. Again, $h$ and $\lambda$ are the smoothing parameters associated with the continuous and discrete variables in $X$, respectively.

## Bandwidth Selection

An important aspect of nonparametric estimation methods is the selection of the smoothing parameters, i.e. $h_0$, $h$, and $\lambda$ in conditional density estimation and $h$ and $\lambda$ in regression estimation. While the choice of kernel function does not impact the results in a meaningful way, different bandwidths can have drastically different results. For sound analysis, it is recommended that one use a data-driven method for selecting the bandwidths. For the purpose of this investigation, I use cross-validation methods described in Li and Racine (2007). Cross-validation is a method by which the data is partitioned into training data and evaluation data; the training data is used to fit the model and the evaluation data is then used to assess the model's performance. I use variations of leave-one-out cross-validation, a process where the evaluation data is one observation and the training data is $n - 1$ observations. The process is repeated $n$ times and then I average the leave-one-out estimates for a given value of the bandwidth vector.

For local linear estimation, I use least-squares cross-validation (LSCV). LSCV selects $h$ and $\lambda$ to minimize the the following cross-validation objective function (Li and Racine 2007):

$$\min_{h,\lambda} CV(h,\lambda) = n^{-1} \sum_{i=1}^{n} (Y_i - \hat{g}_{-i}(X))^2,$$

where $\hat{g}_{-i}(X)$ is the leave-one-out estimator of the local linear estimator.

LSCV in the conditional density context can be computationally intensive. Instead, one can apply maximum likelihood cross-validation (MLCV), which chooses $h_0$, $h$, and $\lambda$ to maximize the following cross-validation objective function (Hall, Li, and Racine 2004):

$$\max_{h_0,h,\lambda} CV(h_0,h,\lambda) = n^{-1}\sum_{i=1}^{n} \ln(\hat{f}_{-i}(Y|X)),$$

where $\hat{f}_{-i}(Y|X)$ is the leave-one-out conditional density estimator.

In the nonparametric setting, the selection of the smoothing parameters is analogous to the model selection in a parametric framework. For the modified Aitchison and Aiken (1976) kernel described above, the bandwidths $\lambda = (\lambda_1, \ldots, \lambda_r)$ are restricted between 0 and 1. When $\lambda_s = 1$ for some discrete variable $X_s^d$, equal weight is being given to each category of $X_s^d$. This means that $X_s^d$ is irrelevant in the prediction of $\hat{f}(Y^d|X)$ (or $\hat{g}(X)$). In this case, $X_s^d$ has been "smoothed" out of the estimation. When $\lambda_s = 0$, the modified Aitchison and Aiken (1976) kernel simply turns into an indicator function. Similarly, for continuous variables, if the cross-validation procedure selects a very large value for $h_s$ (the bandwidth for $X_s^c$), such that $X_s^c$ gets smoothed out, then $X_s^c$ is deemed irrelevant in the estimation of $\hat{f}(Y^d|X)$ (or $g(X)$).

## Outcome Variables

I consider four categories of pharmaceuticals, namely antidepressants, antipsychotics, benzodiazepines, and any medication for mental illness, which includes the former three types and medications for alcohol and substance abuse. Utilization of pharmaceuticals is measured in two ways. Firstly, respondents are asked whether or not they have taken a given drug in the past two days. The resulting variable is binary, taking a value of 1 if their response is "yes" and 0 otherwise. Secondly, having taken a given drug, the interviewers ask the respondents how many medications they have taken in the last two days. This variable is an ordered discrete variable ranging from "1" to "4 or more".

I consider three types of mental health service providers, namely psychiatrists, general practitioners (GPs), and psychologists. Respondents are asked if they had visited or had contact with a given service provider within the past twelve months. If the respondent answers "yes", they are further asked how many visits and the approximate length of each visit. Therefore, I consider two measures for service utilization. Firstly, I consider a binary variable taking a value of 1 if the respondent visited a provider over the past twelve months and 0 otherwise. Secondly, I look at the total number of hours spent with a provider over the past twelve months, conditional on the respondent having had contact with the given professional.

## Predictor Variables

Insurance coverage is measured by a binary variable taking a value of 1 if the individual has insurance that pays for all or part of prescription medications and 0 otherwise. Following Hurley and Mulvale (2008), I control for health, mental health, socioeconomic, demographic, and social support variables. The health variables I consider are self-assessed health (SAH), the presence of any comorbid condition (CC), overweight, and smoker type (SMK). SAH is five point scale ranging from "poor" (SAH=1) to "excellent" (SAH=5). CC is a binary variable taking a value of 1 if the respondent has a comorbid condition and zero otherwise. Overweight is a variable that equals 1 is the individual has a body mass index (BMI) greater than 25 and 0 otherwise. SMK is a six point scale ranging from "Daily smoker" (SMK=1) to "Never smoked" (SMK=6). The CCHS-MH also contains derived variables indicating whether or not an individual meets the criteria for depression and anxiety based on the World Mental Health - Composite International Diagnostic Interview Instrument. In addition, I control for self-assessed mental health (SAMH) measured by a five point scale similar to SAH.

I include a number of demographic variables including age, sex, marital status, immigrant status, and an urban/rural measure. The socioeconomic control variables I consider are family-adjusted household income and education. Family-adjusted household income is a poverty measure defined by Statistics Canada that adjusts income based on family size, taking into account the number of dependents an income must support. To calculate the family-adjusted income, I simply divide the total household income by the square root of the number of of persons in the household. An individual's education level is measured on a four point scale taking a value of 1 if they did not finish high school, 2 if they have high school, 3 if they have some post-secondary education, and 4 if they are a post-secondary graduate.

Finally, I include a measure of the respondent's social support system. The social provision scale is a derived score ranging from 10 to 40, with a score of 10 indicating that the respondent has a poor social support system. The scale takes into account the respondent's ability to confide in someone outside of health care providers and various aspects of their relationship, e.g. take part in activities together, share the same beliefs, and admiration for one another. The models and methods used to estimate them are summarized in Table 1 in Appendix A

# Results

Referenced tables and figures can be found in Appendices A and B, respectively.

## Summary Statistics

Tables 2 to 5 present the summary statistics for the outcome variables in Models 1 to 4, respectively. The 2012 CCHS-MH is a community-based study, therefore, I observe low use of mental health pharmaceuticals. The most common type of medication used was an antidepressant at 5.5 percent (Table 2). Focusing solely on those who have taken a medication in Model 2 affects the working sample size. Table 3 gives the sample size and percentages for each type of medication. Due to the small sample size, cell counts for the number of certain medications taken did not meet the requirements for the Statistics Canada Research Data Centre. The number of medications taken was then measured as a binary variable taking a value of "one" or "two or more" for antidepressants, antipsychotics, and benzodiazepines. For the category of "any medication", I was able to look at the use of medications up to "four or more". Out of those who took a respective medication, approximately 14 percent took two or more antidepressants, 18 percent took two or more antipsychotics, 10 percent took two or more benzodiazepines, and 35 percent took two or more medications in total.

Similarly, I observe low levels of use of health care professionals for mental health issues. Approximately 2 percent of the sample visited a psychiatrist and 2 percent visited a psychologist (Table 4). The most common provider used for mental health problems was a GP, with an average time spent over twelve months of 98.64 hours (Table 5).

Tables 6 and 7 shows the summary statistics for the discrete and continuous predictor variables, respectively. The majority (77.9 percent) of respondents had insurance that covered all or part of their prescription drug costs. Approximately 5 percent of the sample met the criteria for depression and approximately 2 percent met the criteria for anxiety. Despite 57 percent reporting having a comorbid condition, over 60 percent of respondents claimed to be in very good or excellent overall health and mental health. Approximately 78 percent of the sample are non-smokers with 40 percent having never smoked. 43.87 percent of the sample reported a BMI over 25 being classified as overweight or obese.

The sample was closely split between males (49.3 percent) and females (50.7 percent) and the average age of respondents was 43.86 years (Table 7). 58.67 percent of the sample was married and 21.71 percent were single. Approximately three-quarters of the sample were born in Canada with 71.24 percent of all respondents living in a census metropolitan area. 62.11 percent of the sample hold a post-secondary degree and the average family-adjusted income was $47,652.26 (Table 7). The range of the social provision score is 10 to 40. With an average score of 36.26 and a standard deviation of 4.15, most of the sample is clustered around the moderate to strong social support scores.

## Model 1 - Binary Use/No Use of Prescription Medications

Table 8 presents the results from the nonparametric conditional density estimation with binary use/no use of medications as the outcome variable versus the discrete predictor variables (all other variables held constant at their means and modes). The values presented in the tables are the percent differences between the base category of the variable and the other categories. A value of $V$ in the table suggest that individuals in the listed category are $V\%$ more likely than those in the base category to use a given drug. A value of $V = 0$ means that there is no difference between categories, i.e. the variable is irrelevant.

The base category for insurance is "No". Therefore, individuals who hold supplemental insurance to cover medications are 13.48 percent more likely to take antidepressants, twice as likely to take antipsychotics, and 11.72 percent more likely to take any medication for mental illness than those who do not hold insurance. Insurance, however, has no influence on whether someone will take a benzodiazepine. Meeting the characteristics for depressions and anxiety has a small positive or no impact on the use of all medications, while those who report being in poor mental health are far more likely to use all four categories of medications compared to those in excellent mental health. People who reported having poor mental health were over 16 times more likely to take antidepressants, were over 350 times more likely to take antipsychotics, were over 8 times more likely to take a benzodiazepine, and 19 times more likely to take any medication for mental illness compared to those with excellent SAMH. Having a comorbid condition increases the probability of taking a medication for mental illness. Those who reported having a comorbid condition were approximately 6 times more likely to take an antidepressant, 8 times more likely to take an antipsychotic, 3.5 times more likely to take a benzodiazepine, and 6 times more likely to take any medication for mental illness.

Males are less likely to take antidepressants (-43.18 percent) and benzodiazepine (-74.33 percent) and are more likely to take antipsychotics (9.2 percent). Widowers are 8.54 percent more likely to take antidepressants, are 11.78 percent more likely to take benzodiazepines, and 9.96 percent more likely to take any medication for mental illness (including alcohol and substance abuse). Similarly, individuals who are divorced are more likely to use an antidepressant, a benzodiazepine, and any drug for mental illness. Married people have a higher probability of using antipsychotics compared to all other marital statuses. Individuals born outside of Canada are less likely to use antidepressants (-38.54 percent), benzodiazepines (-80.28 percent), and any medication for mental illness (-32.22 percent) and are more likely to use antipsychotics.

Figure 1 shows the estimated conditional probabilities of using a prescription medication versus age. Figure 1a shows a quadratic relationship between age and the likelihood of using an antidepressant. The conditional probability rises from ages 15 years to 50 years and begins to decrease. The relationship between age and the use of antipsychotic medications is bi-modal, with one peak at age 35 and the second peak after the age of 80 (Figure 1b). The conditional probability of using a benzodiazepine increases from age 15 to age 64 and then begins to decrease.

Figure 2 shows the relationship between social provision score and the conditional probability of using a prescription medication for mental illness. Figures 2a to 2d show the same relationship: those with low social provision scores have a higher probability of using mental health pharmaceuticals than those with high scores. In each of these figures, there is a sharp drop in likelihood from a score of 10 to 20, with a slower decrease from 20 to 40. This suggests that even small amounts of support can reduce the likelihood of using medications for mental illness. Similar to Mulvale and Hurley (2008), I found that family-adjusted income in irrelevant in the estimation of the binary use/no use measure of drug utilization.

## Model 2 - Number of Medications Taken in the Past Two Days

Model 2 examines the use of mental health pharmaceuticals, conditional on having taken a given drug. Tables 9 and 10 present $\hat{f}\,(\text{No. Meds Used} \geq 2|X, \text{Used Med.} = \text{ YES})$ versus discrete predictor variables (all other variables held constant at their medians/modes) for antidepressants, antipsychotics, and benzodiazepines and $\hat{f}\,(\text{No. of Any Meds} = 1|X, \text{Used Med.} = \text{ YES})$, $\hat{f}\,(\text{No. of Any Meds} = 2|X, \text{Used Med.} = \text{ YES})$, $\hat{f}\,(\text{No. of Any Meds} = 3|X, \text{Used Med.} = \text{ YES})$, and $\hat{f}\,(\text{No. of Any Meds} \geq 4|X, \text{Used Med.} = \text{ YES})$ versus discrete predictor variables, respectively. Conditional on using a respective medication, individuals with insurance are 4.74 percent more likely to use two or more antidepressants, 43.87

percent more likely to use two or more antipsychotics, and 424.30 percent more likely to use a benzodiazepine. Even though insurance had no effect in the likelihood of using a benzodiazepine (Table 8), conditional on having taken a benzodiazepine, those with insurance are more than five times more likely to take more benzodiazepines. In Table 10, there are two things to consider. Firstly, what is the percent change between categories of a given variable. For those who have taken any medication for mental illness, those with insurance are 2.21 less likely to take just one medication, are 3.42 percent more likely to take two medications, 7.61 percent more likely to take three medications and 10.66 more likely to take four or more medications. Secondly, it is important to observe how these values change as the number of medications taken increases. There is a positive gradient between the percentage change in the probability of taking medication and insurance, i.e. the percent change in the probability of taking medication between insurance statuses increases as the number of medications increases. This means that insurance has a larger impact on taking four or more medications than it does taking two medications.

Individuals in excellent overall health are less likely to use antipsychotics than those in the other four categories and those with a comorbid condition are approximately 6,728 times more likely to use an antipsychotic (Table 9). In Table 10, I observe a negative gradient for self-assessed health and self-assessed mental health for $\hat{f}(\text{No. of Any Meds} = 3|X, \text{Used Med.} = \text{ YES})$ and $\hat{f}(\text{No. of Any Meds} \geq 4|X, \text{Used Med.} = \text{ YES})$. The percentage change in conditional probability is decreasing from "Poor" SAH to "Very Good" SAH compared to "Excellent" SAH. Furthermore, within the categories "Poor", "Fair", and "Good" there is an increase in the percentage change in conditional probabilities as the number of medications taken increases. A similar pattern is observed for those with a comorbid condition. Those with a comorbid condition are 9.39 percent less likely to take only one medication but are 164.62 percent more likely to take 4 or more medications. Those who never smoked are more likely to take two or more benzodiazepines. While the long-term effects of smoking increase anxiety, smoking can offer an immediate (although temporary) relief of anxiety (Mental Health Foundation 2017). This may help to explain the difference in the likelihood of using two or more benzodiazepines between daily smokers and those who never smoked. For overall medication use, the story changes. In Table 10, smokers are more likely than those who never smoked to take four or more medications.

Sex is not relevant in the use of two or more antipsychotics or benzodiazepines, while males are 16.60 percent less likely to take two or more antidepressants (Table 9). Marital status was irrelevant in the estimation of $\hat{f}(\text{No. of Meds}|X, \text{Used Med.} = \text{ YES})$ for antidepressants, antipsychotics, and benzodiazepines. Looking at total utilization, married people are more likely to use four or more medications compared to all other marital statuses. Interestingly, individuals with at least a high school diploma are more likely to to take two or more antipsychotics and are more likely to take four or more total medications than those with less than high school. In Table 8, individuals with less than high school were more likely to take antipsychotics and were more likely to take any medication than those with more years of education. One explanation for this might be that, among those who take antipsychotics, individuals with higher levels of schooling might be more likely to adhere to a prescription, making it more likely that they took more doses in the past two days. There appears to be no difference between urban and rural dwellers in the use of more antidepressants and benzodiazepines. Individuals living in an urban centre are 55.55 percent less likely to use antipsychotics.

Figure 3 shows $\hat{f}\,(\text{No. Meds Used} \geq 2|X, \text{Used Med.} = \text{ YES})$ versus age for antidepressants and antipsychotics; age was irrelevant in estimating $\hat{f}\,(\text{No. antipsychotics} \geq 2|X, \text{Used antipsychotics} = \text{ YES})$. Both Figures 3a and 3b show a negative quadratic relationship where the probability of taking two or more antidepressants and the probability of taking two or more benzodiazepines increases until middle-age (40-60 years of age) and then decreases. Figure 4 shows $\hat{f}\,(\text{No. of Any Meds} = 2|X, \text{Used Med.} = \text{ YES})$, $\hat{f}\,(\text{No. of Any Meds} = 3|X, \text{Used Med.} = \text{ YES})$, and $\hat{f}\,(\text{No. of Any Meds} \geq 4|X, \text{Used Med.} = \text{ YES})$ versus age. As the number of medications taken in the past two days increases the the mode moves to younger ages, with individuals in their thirties having the highest probability of taking four or more medications for mental illness.

In Model 1, family-adjusted income was shown to have no effect on the probability of taking any type of medication. However, Figures 5 and 6 and show that family-adjusted income influences the number of antidepressants, benzodiazepines, and any medications taken. Figure 5a shows that the probability of taking two or more antidepressants is higher for those with a family-adjusted income below $200,000 and sharply decreases after that. For benzodiazepines (Figure 5b), the probability of taking two or more medications is highest for those with a family-adjusted income of approximately $230,000. In Figure 6, the probability of taking more medications increases for low family-adjusted income households and decreases for higher family-adjusted income earners as the number of drugs taken increases. This results in a near negative linear relationship between $\hat{f}\,(\text{No. of Any Meds} \geq 4|X, \text{Used Med.} = \text{ YES})$ and family-adjusted income.

Figures 7 and 8 show $\hat{f}\,(\text{No. Meds Used}|X, \text{Used Med.} = \text{ YES})$ versus SPS for antipsychotics and any medication. Among those who take antipsychotics, individuals with strong social supports are more likely to take two or more antipsychotics in the past two days. The relationship displayed in Figure 7 is positive and almost linear. Antipsychotics are typically prescribed in severe cases of mental illness (e.g. schizophrenia, bipolar disorder, psychotic depression). It is possible that those with strong social supports have additional help that keeps them on track to take their prescribed medications and are therefore more likely to take more antipsychotics. Figure 8 shows that the likelihood of that the total number of medications taken for mental illness increases as the social provision score decreases.

## Model 3 - Visited a Health Care Provider in the Past Twelve Months Yes/No

Similar to Mulvale and Hurley (2008), I found that insurance had no effect on the use of psychiatrists and GPs (Table 11). Contrary to their findings, I observed that insurance was positively related with using a psychologist. Using prescription drug insurance as a proxy for insurance which covers community-based mental health services, the nonparametric estimation results showed that individuals with insurance are 21.77 percent more likely to use a psychologist. Mental health status has an impact on the use of psychiatrists and psychologists. Individuals who meet the characteristics for depression are 11 times more likely to visit a psychiatrist and approximately 6 times more likely to visit a psychologist. In addition, there is a clear negative gradient for self-assessed mental health in terms of percent change in conditional probabilities between each listed category and the base category "Excellent". The presence of a comorbid condition increases the likelihood of seeing a psychiatrist and a psychologist.

The results also show that males are more likely to visit a psychiatrist while women are more likely to visit a psychologist. Married individuals are more likely to visit a psychiatrist than any other marital status. Immigrants are 5.5 percent less likely to visit a psychiatrist and 23.25 percent less likely to visit a psychologist.

Figure 9 shows the estimated conditional probability of visiting a health care provider versus age (all other variables held constant at their medians/modes). Each panel shows a distribution with a positive skew with a mode of 40 years for psychologists and GPs and a mode of 30 for psychologists. Figure 10 displays the estimated conditional probabilities versus social provision score. The pattern observed is comparable to Model 1 above - the probability of using a psychiatrist or a GP for mental health issues is higher for those with low social provision scores. The probability decreases quickly from scores of 10 to 20 then stabilizes. This would suggest that even small amounts of social support reduce the likelihood of visiting a publicly funded health care professional for mental health reasons. Social provision, however, was irrelevant in estimating the probability of visiting a psychologist. Similar to the binary measure for drug utilization, family-adjusted income has no impact on the probability of use of health care providers.

### Model 4 - Number of Hours Spent with a Health Care Provider in the Past Twelve Months

Results from local linear regression estimating the impact of insurance on the number of hours spent with a health care professional are presented in Table 12. The values in the table are the percent change between those with insurance and those without. Conditional on having visited a given health care professional, individuals who hold prescription drug insurance spent 8.96 percent more time with a psychiatrist and 12.91 percent more time with a psychologist, on average.

## Conclusion

The purpose of this paper was to study the effect of supplemental insurance on the use of mental health goods and services. Results from nonparametric conditional density estimation showed that insurance positively affect the probability of using mental health pharmaceuticals as well as the intensity of use of all categories of medications. I also showed that individuals with insurance are more likely to visit psychiatrists and psychologists for mental health issues and spend more time with these types of providers compared to those without insurance. It is clear that insurance positively affects the use and the intensity of use of mental health care pharmaceuticals and providers. What I am unable to distinguish is whether this utilization is due to moral hazard or that insurance is opening access to necessary mental health care goods and services. If it is the latter, then the distribution of mental health care services based on needs would be unfairly distributed benefitting those with supplemental insurance. In addition, the analysis showed that individuals with a comorbid condition and those with poor social supports are more likely to use health care goods and services. Results from nonparametric conditional density estimation suggest that even small amounts of social support reduce the likelihood of using mental health pharmaceuticals and reduces the intensity of use.

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## Appendix A – Tables

Table 1 - Models and Methods

| Model | Object | Method |
|---|---|---|
| 1 | $\hat{f}$ (Used Antidepressant$\|X$) | Nonparametric CPDF |
| | $\hat{f}$ (Used Antipsychotic$\|X$) | |
| | $\hat{f}$ (Used Benzodiazepine$\|X$) | |
| | $\hat{f}$ (Used Any Medication$\|X$) | |
| 2 | $\hat{f}$ (No. ADEP Used$\|X$, Used ADEP $=$ YES)* | Nonparametric CPDF |
| | $\hat{f}$ (No. APSY Used$\|X$, Used APSY $=$ YES) | |
| | $\hat{f}$ (No. BENZ$\|X$, Used BENZ $=$ YES) | |
| | $\hat{f}$ (No. Any Meds$\|X$, Used Any Med $=$ YES) | |
| 3 | $\hat{f}$ (Visited Psychiatrist$\|X$) | Nonparametric CPDF |
| | $\hat{f}$ (Visited GP$\|X$) | |
| | $\hat{f}$ (Visited Psychologist$\|X$) | |
| 4 | $E$(Hrs with Psychiatrist$\|X$, Visited Psychiatrist $=$ YES) | Local Linear |
| | $E$(Hrs with GP$\|X$, Visited GP $=$ YES) | |
| | $E$(Hrs with Psychologist$\|X$, Visited Psychologist $=$ YES) | |

*ADEP = Antidepressant, APSY = Antipsychotic, and Benz = Benzodiazepine.

Table 2 - Summary Statistics - Used a Medication in the Past Two Days

| Medication Type | Percent |
|---|---|
| Antidepressant | |
| Yes | 5.50 |
| No | 94.50 |
| Antipsychotic | |
| Yes | 0.90 |
| No | 98.61 |
| Benzodiazepines | |
| Yes | 1.30 |

| | |
|---|---|
| No | 98.70 |
| | |
| Any drug | |
| Yes | 6.70 |
| No | 93.30 |

Table 3 - Summary Statistics - Number of Medications Taken in the Past Two Days (Conditional on Having Taken a Given Medication)

| Medication Type | Sample Size | Percent |
|---|---|---|
| No. of Antidepressants | 1562 | |
| 1 | | 85.82 |
| 2 or more | | 14.18 |
| | | |
| No. of Antipsychotics | 313 | |
| 1 | | 82.50 |
| 2 or more | | 17.50 |
| | | |
| No. of Benzodiazepines | 483 | |
| 1 | | 90.00 |
| 2 or more | | 10.00 |
| | | |
| No. of Medications | 1993 | |
| 1 | | 65.40 |
| 2 | | 18.70 |
| 3 | | 5.40 |
| 4 or more | | 2.90 |

Table 4 - Summary Statistics - Visited a Health Care Professional for Mental Illness in Past Twelve Months

| Professional | Percent |
|---|---|
| Visited a psychiatrist | |
| Yes | 2.00 |
| No | 97.99 |

| | |
|---|---|
| Visited a GP | |
| Yes | 6.80 |
| No | 93.20 |
| | |
| Visited a psychologist | |
| Yes | 2.21 |
| No | 97.78 |

Table 5 - Summary Statistics - Number of Hours Spent with Health Care Professional in the Past Twelve Months (Conditional on Having Visited a Given Professional)

| Professional | Sample Size | Mean | Std. Dev. |
|---|---|---|---|
| Hrs with a psychiatrist | 639 | 14.37 | 103.4 |
| Hrs with a GP | 1901 | 98.64 | 33.5 |
| Hrs with a psychologist | 632 | 14.40 | 40.5 |

Table 6 - Summary Statistics - Discrete Predictor Variables

| Variable Description | Percent |
|---|---|
| Insurance | |
| Yes | 77.9 |
| No | 22.1 |
| | |
| Depression | |
| Yes | 5.16 |
| No | 94.84 |
| | |
| Anxiety | |
| Yes | 2.26 |
| No | 97.74 |
| | |
| Comorbid condition | |

| | |
|---|---|
| Yes | 57.01 |
| No | 42.99 |
| | |
| SAMH | |
| Poor | 1.30 |
| Fair | 5.49 |
| Good | 26.61 |
| Very Good | 41.69 |
| Excellent | 24.92 |
| | |
| SAH | |
| Poor | 1.53 |
| Fair | 7.03 |
| Good | 28.48 |
| Very Good | 40.50 |
| Excellent | 22.45 |
| | |
| Smoker Type | |
| Daily | 15.50 |
| Occasional | 5.50 |
| Former Daily | 23.20 |
| Former Occasional | 15.70 |
| Never | 40.10 |
| | |
| Overweight | |
| Yes | 43.87 |
| No | 56.13 |
| | |
| Sex | |
| Male | 49.3 |
| Female | 50.7 |
| | |
| Marital Status | |
| Married | 58.67 |
| Common Law | 13.47 |
| Widower | 1.33 |

| | |
|---|---|
| Separated/divorced | 4.83 |
| Single | 21.71 |
| | |
| Immigrant | |
| Yes | 25.12 |
| No | 74.88 |
| | |
| Urban | |
| Yes | 71.24 |
| No | 28.76 |
| | |
| Education | |
| < high school | 15.66 |
| High School | 15.26 |
| Some post sec. | 6.97 |
| Post Sec. Grad | 62.11 |

Table 7 - Summary Statistics - Continuous Predictor Variables

| Variable Description | Mean | Std. Dev. |
|---|---|---|
| Age (Years) | 43.86 | 16.96 |
| Family-adjusted income ($) | 47,652.26 | 53,576.59 |
| Social provision score | 36.26 | 4.15 |

Table 8 - Percent Change in $\hat{f}\ (Used\ Med. = YES|X)$ Versus Discrete Predictor

| Variable | Antidepressants | Antipsychotics | Benzodiazepines | Any |
|---|---|---|---|---|
| Insurance | | | | |
| Yes | 13.48 | 100.03 | 0 | 11.72 |
| | | | | |
| Depression | | | | |
| Yes | 2.1 | 2.22 | 0.33 | 1.57 |
| | | | | |
| Anxiety | | | | |

| | | | | |
|---|---|---|---|---|
| Yes | 0.2 | 0 | 1.37 | 0.26 |
| | | | | |
| SAH | | | | |
| Poor | 0.81 | -54.26 | 14.43 | -3.08 |
| Fair | 2.01 | -33.9 | 38 | -2.97 |
| Good | 5.03 | -59.21 | 31.35 | 0.07 |
| Very Good | -6.17 | -68.27 | -54.29 | -11.01 |
| | | | | |
| SAMH | | | | |
| Poor | 1518.88 | 34801.17 | 749.27 | 1801.01 |
| Fair | 1308.77 | 5167.88 | 459.78 | 1407.42 |
| Good | 743.58 | 2364.07 | 183.71 | 794.17 |
| Very Good | 256.3 | 585.69 | 58.5 | 275.25 |
| | | | | |
| Comorbid Condition | | | | |
| Yes | 494.62 | 720.12 | 274.63 | 513.72 |
| | | | | |
| Smoker Type | | | | |
| Daily | 7.37 | -6.7 | -0.43 | 8.2 |
| Occasional | 7 | -4.71 | -6.28 | 5.85 |
| Former Daily | 9.58 | 19.07 | -4.37 | 8.89 |
| Former Occasional | 21.56 | -13.48 | -0.58 | 18.45 |
| | | | | |
| Overweight | | | | |
| Yes | 4.48 | 0 | 0 | 1.95 |
| | | | | |
| Sex | | | | |
| Male | -43.18 | 9.2 | -74.33 | -33.78 |
| | | | | |
| Marital Status | | | | |
| Common-Law | 0.57 | -35.23 | 5.53 | 1.99 |
| Widowed | 8.54 | -3.13 | 11.78 | 9.96 |
| Divorced | 6.08 | -17.17 | 4.15 | 5.73 |
| Single | -0.99 | -18.11 | 1.39 | -0.97 |
| | | | | |
| Immigrant | | | | |

| | | | | |
|---|---|---|---|---|
| Yes | -38.54 | 14.69 | -80.28 | -32.22 |
| | | | | |
| Education | | | | |
| Secondary | -9.5 | -11.77 | 22.04 | -12.53 |
| Some Post Sec. | -10.4 | -1.68 | -22.77 | -14.13 |
| Post Sec. Grad | 1.99 | -9.02 | 1.02 | -0.65 |
| | | | | |
| Urban | | | | |
| Yes | 0.23 | 0 | 0.38 | 0.18 |

Table 9 - Percent Change in $\hat{f}\ (No. Meds\ Used \geq 2|X, Used\ Med. = YES)$ Versus Discrete Predictor for Antidepressants, Antipsychotics, and Benzodiazepines

| Variable | Antidepressants ($n = 1562$) | Antipsychotics ($n = 313$) | Benzodiazepines ($n = 483$) |
|---|---|---|---|
| Insurance | | | |
| Yes | 4.74 | 43.87 | 424.30 |
| | | | |
| Depression | | | |
| Yes | 13.47 | -8.39 | 120.64 |
| | | | |
| Anxiety | | | |
| Yes | 6.46 | 0.00 | 9.40 |
| | | | |
| SAH | | | |
| Poor | 7.03 | 192.26 | 576.52 |
| Fair | 12.61 | 113.00 | -1.72 |
| Good | 2.50 | 163.64 | -50.89 |
| Very Good | 2.55 | 98.47 | 68.34 |
| | | | |
| SAMH | | | |
| Poor | 2.80 | 5.80 | -3.73 |
| Fair | -0.43 | 4.61 | 35.81 |
| Good | 9.94 | -9.09 | -13.97 |
| Very Good | -3.97 | -3.33 | -12.66 |

| | | | |
|---|---|---|---|
| CC | | | |
| Yes | 0.00 | 672789.50 | 0.00 |
| | | | |
| Smoker Type | | | |
| Daily | 3.61 | -19.10 | -40.24 |
| Occasional | -0.44 | -8.93 | -29.21 |
| Former Daily | -0.11 | -10.12 | -28.79 |
| Former Occ. | 1.93 | 1.45 | -32.26 |
| | | | |
| Overweight | | | |
| Yes | 0.00 | 20.82 | 0.00 |
| | | | |
| Sex | | | |
| Male | -16.60 | 0.00 | 0.00 |
| | | | |
| Marital status | | | |
| Common-Law | 0.00 | 0.00 | 0.00 |
| Widowed | 0.00 | 0.00 | 0.00 |
| Divorced | 0.00 | 0.00 | 0.00 |
| Single | 0.00 | 0.00 | 0.00 |
| | | | |
| Immigrant | | | |
| Yes | 0.26 | 0.00 | 0.00 |
| Education | | | |
| Secondary | -2.01 | 44.72 | -6.66 |
| Some Post Sec. | -0.34 | 27.56 | 45.47 |
| Post Sec. Grad | -2.74 | 29.98 | 3.19 |
| Urban | | | |
| Yes | 0.00 | -55.22 | 0.00 |

Table 10 - Percent Change in $\hat{f}\ (No. Meds\ Used|X, Used\ Med. = YES)$ Versus Discrete Predictor for Any Medication

| Variable | $Y = 1$ | $Y = 2$ | $Y = 3$ | $Y \geq 4$ |
|---|---|---|---|---|
| Insurance | | | | |

| | | | | |
|---|---|---|---|---|
| Yes | -2.21 | 3.42 | 7.61 | 10.66 |
| | | | | |
| Depression | | | | |
| Yes | -1.2 | 1.93 | 10.19 | 100 |
| | | | | |
| Anxiety | | | | |
| Yes | -0.11 | 0.17 | 0.84 | 13.55 |
| | | | | |
| SAH | | | | |
| Poor | -4.39 | 8.14 | 47.56 | 241.28 |
| Fair | -6.12 | 17.8 | 30.03 | 26.95 |
| Good | -4.66 | 13.33 | 16.88 | 20.66 |
| Very Good | 1.48 | -2.46 | -17.9 | -18.88 |
| | | | | |
| SAMH | | | | |
| Poor | -6.47 | 8.76 | 61.24 | 856.57 |
| Fair | -2.54 | 3.06 | 26.27 | 189.45 |
| Good | -5.96 | 12.98 | 32.89 | -9.76 |
| Very Good | -1.76 | 9.96 | -11.23 | -14.82 |
| | | | | |
| Comorbid Condition | | | | |
| Yes | -9.39 | 24.36 | 43.05 | 164.62 |
| | | | | |
| Smoker Type | | | | |
| Daily | -0.15 | -5.81 | 33.52 | 74.66 |
| Occasional | 0.52 | -3.06 | 9.27 | 72.32 |
| Former Daily | 0.27 | -2.44 | 10.64 | 25.58 |
| Former Occasional | -0.75 | 2.58 | 2.42 | -8.09 |
| | | | | |
| Overweight | | | | |
| Yes | -1.94 | 6.28 | 10.55 | -44.6 |
| | | | | |
| Sex | | | | |
| Male | 0 | 0 | 0 | 0 |
| | | | | |
| Marital status | | | | |

| | | | | |
|---|---|---|---|---|
| Common-Law | -0.03 | 4.84 | -23.16 | -72.88 |
| Widowed | 0.21 | -4.73 | 10.23 | -52.08 |
| Divorced | -4.42 | 12.02 | 6.42 | -55.33 |
| Single | -2.77 | 8.89 | -3.79 | -49.94 |
| | | | | |
| Immigrant | | | | |
| Yes | 0.12 | -0.19 | -0.51 | -1.48 |
| | | | | |
| Education | | | | |
| Secondary | -0.91 | 3.67 | 6.12 | 103.65 |
| Some Post Sec. | 0.62 | -1.26 | 4.81 | 14.88 |
| Post Sec. Grad | -1.72 | 1.8 | 34.99 | 20.91 |
| | | | | |
| Urban | | | | |
| Yes | 0 | 0 | 0 | 0 |

Table 11 - Percent Change in $\hat{f}\ (Visited\ Professional = YES|X)$ Versus Discrete Predictor Variables

| Variable | Psychiatrist | GP | Psychologist |
|---|---|---|---|
| Insurance | | | |
| Yes | 2.02 | 0 | 21.77 |
| | | | |
| Depression | | | |
| Yes | 1095.62 | 0.69 | 485.44 |
| | | | |
| Anxiety | | | |
| Yes | 977.9 | 0.03 | 305.39 |
| | | | |
| SAH | | | |
| Poor | -9.39 | 0.02 | 9.66 |
| Fair | -8.36 | 0.02 | 11.77 |
| Good | -8.19 | 0.03 | 21.75 |
| Very Good | -14.74 | 0 | 7.15 |
| | | | |
| SAMH | | | |

| | | | |
|---|---|---|---|
| Poor | 34829.52 | 0.56 | 286.89 |
| Fair | 9558.06 | 0.61 | 384.41 |
| Good | 3092.78 | 0.43 | 216.93 |
| Very Good | 748.91 | 0.09 | 65.32 |
| | | | |
| Comorbid Condition | | | |
| Yes | 40.33 | 0 | 9.14 |
| | | | |
| Smoker Type | | | |
| Daily | -32.37 | 0.01 | -7.36 |
| Occasional | -32.98 | 0.01 | -13.48 |
| Former Daily | -31.2 | 0.01 | -12.04 |
| Former Occasional | -39.39 | 0.03 | -10.78 |
| | | | |
| Overweight | | | |
| Yes | -0.09 | 0 | 0 |
| | | | |
| Sex | | | |
| Male | 8.19 | 0 | -35.22 |
| | | | |
| Marital Status | | | |
| Common-Law | -22.44 | -0.01 | -6.23 |
| Widowed | -9.31 | 0.03 | 19.68 |
| Divorced | -13.34 | 0.03 | 4.02 |
| Single | -12.5 | 0.03 | -2.24 |
| | | | |
| Immigrant | | | |
| Yes | -5.5 | 0 | -23.15 |
| | | | |
| Education | | | |
| Secondary | -1.23 | -0.1 | -39.16 |
| Some Post Sec. | 22.83 | -0.08 | -35.03 |
| Post Sec. Grad | 18.39 | -0.02 | 15.4 |
| | | | |
| Urban | | | |
| Yes | 0 | 0 | 0 |

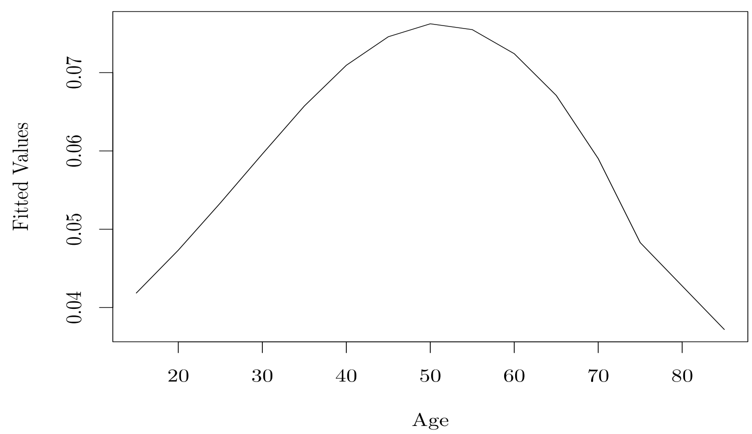
Table 12 - Percent Change in $\hat{E}$ $(Hours\ with\ Professional|X, Visited\ Professional = YES)$ Versus Insurance (All other variables held constant at their medians/modes)

| Variable | Psychiatrist | GP | Psychologist |
|---|---|---|---|
| Insurance | 8.96 | 1.41 | 12.91 |

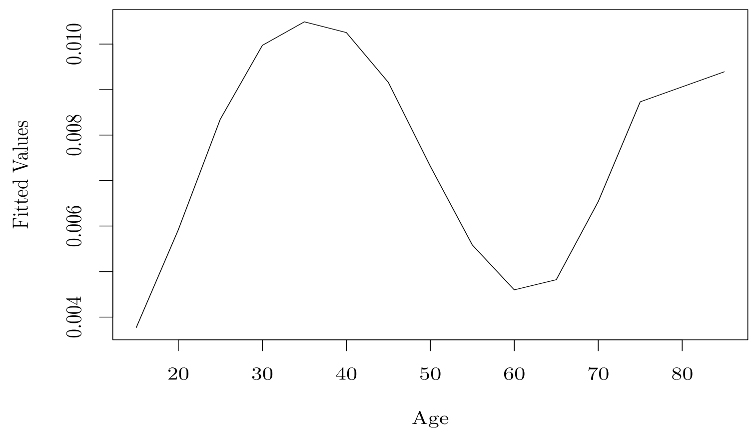
## Appendix B – Figures

Figure 1 - $\hat{f}$ (Used Any Medication $=$ YES$|X$) Versus Age (All other variables held constant at their medians/modes)

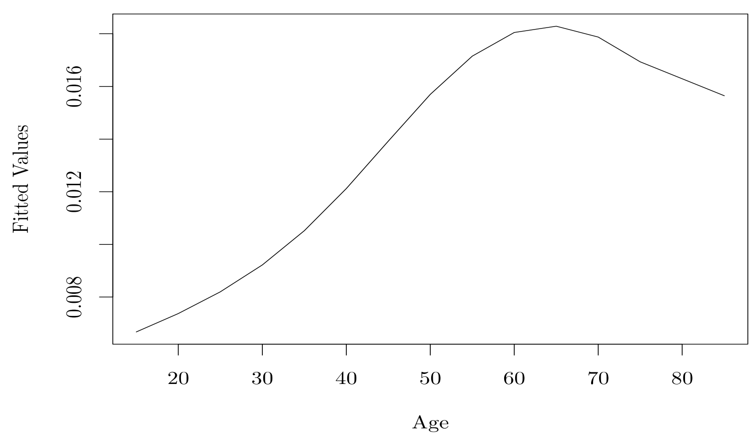
(a) Antidepressants




(b) Antipsychotics




(c) Benzodiazepines




(d) Any Medication

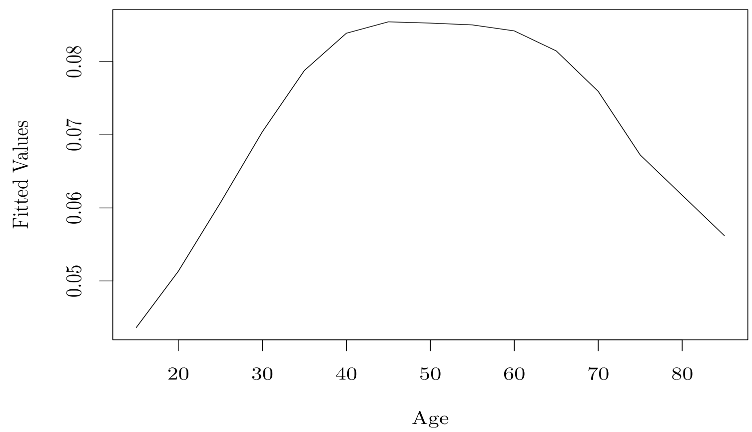
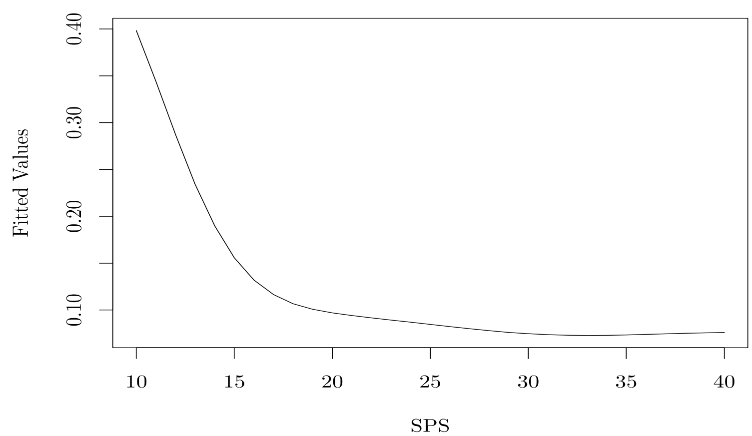
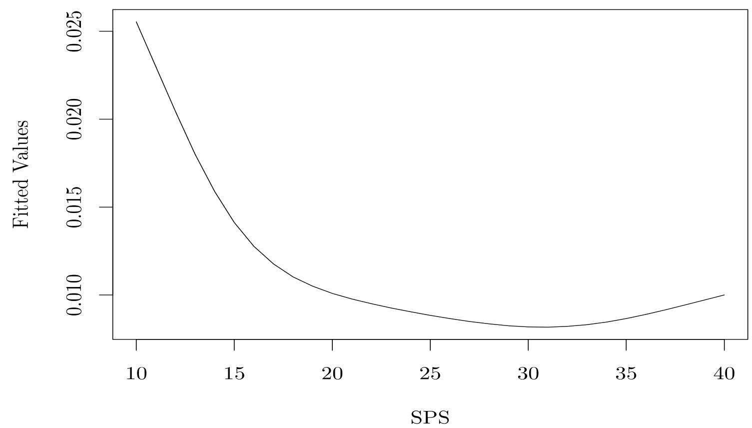



Figure 2 - $\hat{f}$ (Used Medication $=$ YES$|X$) Versus SPS (All other variables held constant at their medians/modes)

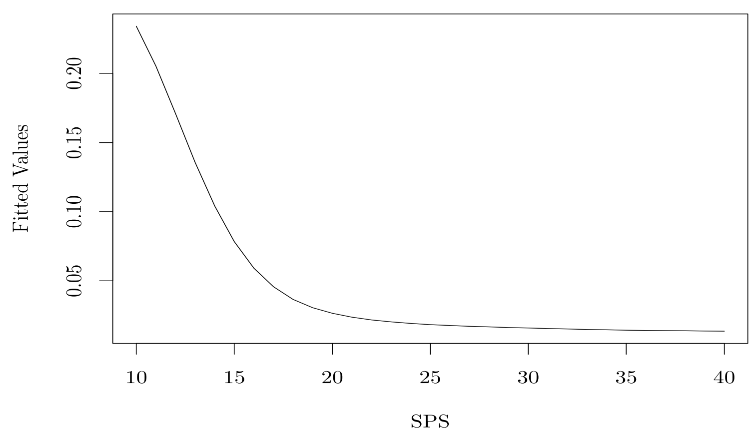
(a) Antidepressants




(b) Antipsychotics




(c) Benzodiazepines




(d) Any Medication

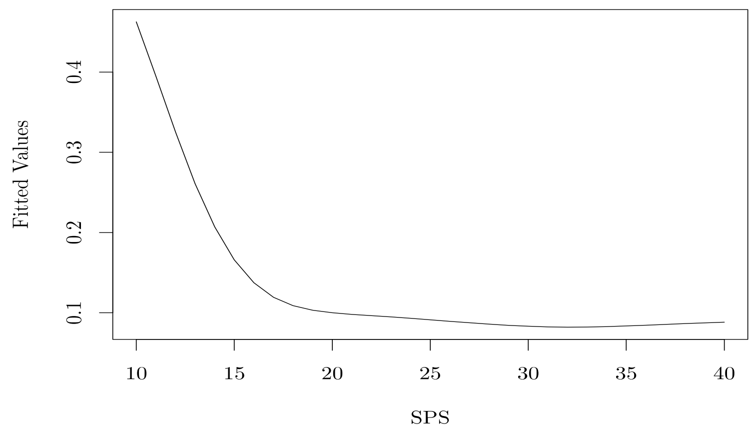
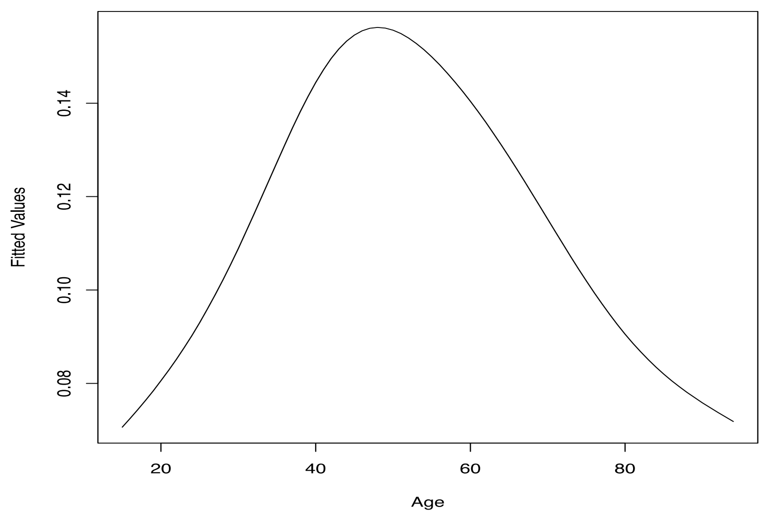



Figure 3 - $\hat{f}$ (No. of Meds $\geq 2|X$, Used Med $=$ YES) Versus Age

(a) Antidepressants




(b) Benzodiazepines

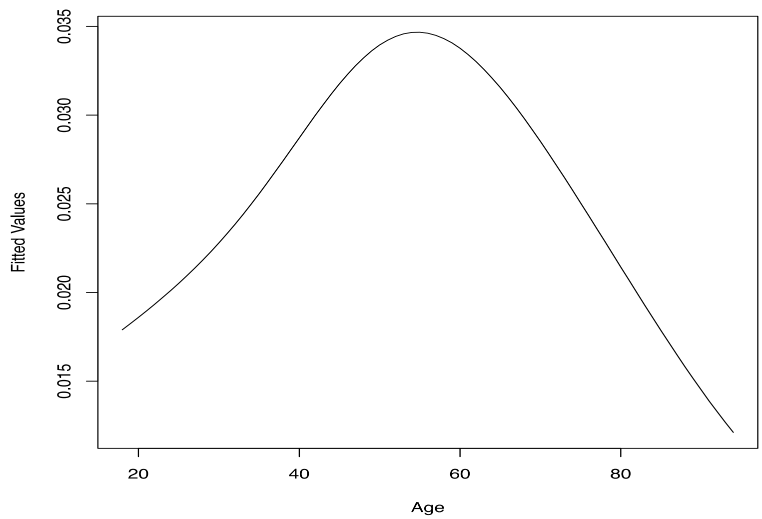
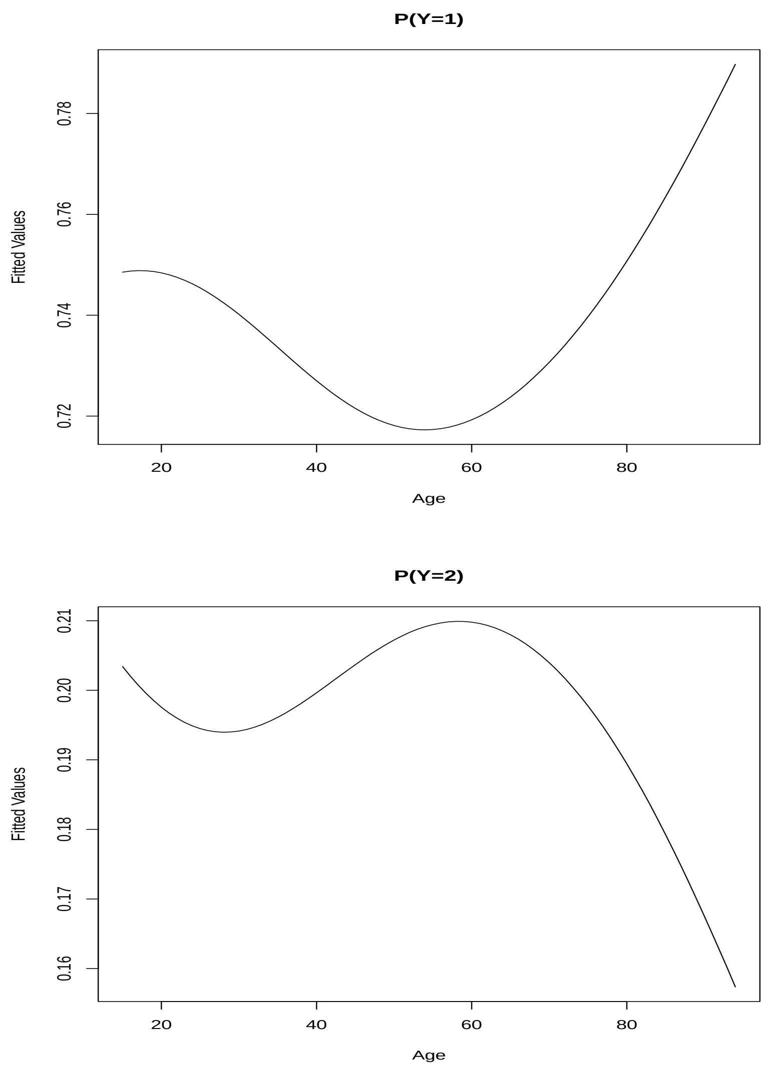



Figure 4 - $\hat{f}$ (No. of Any Medications$|X$, Used Any Medication $=$ YES) Versus Age



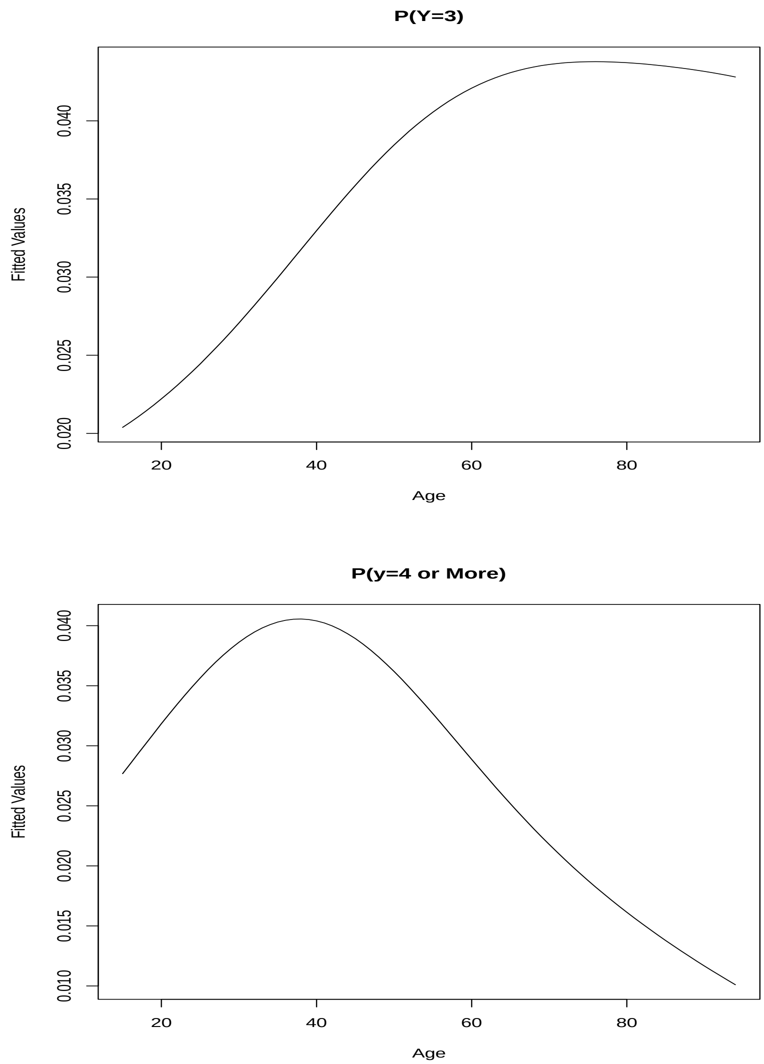
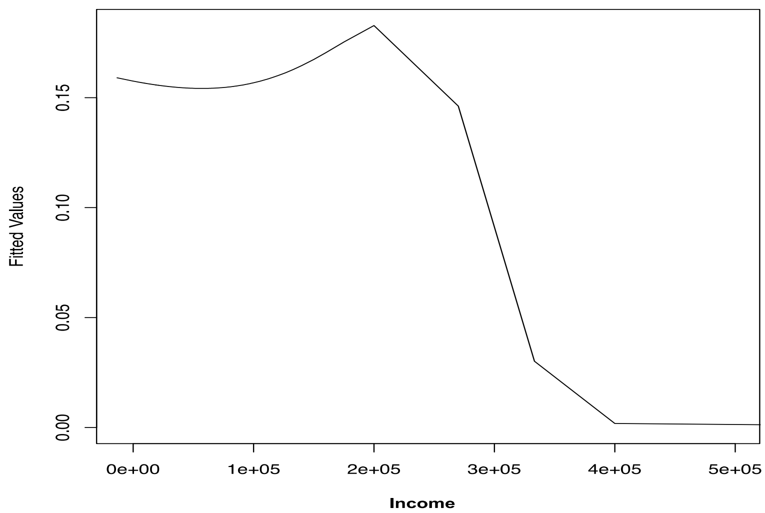



Figure 5 - $\hat{f}$ (No. of Meds $\geq 2|X$, Used Med $=$ YES) Versus Family-Adjusted Income

(a) Antidepressants




(b) Benzodiazepines

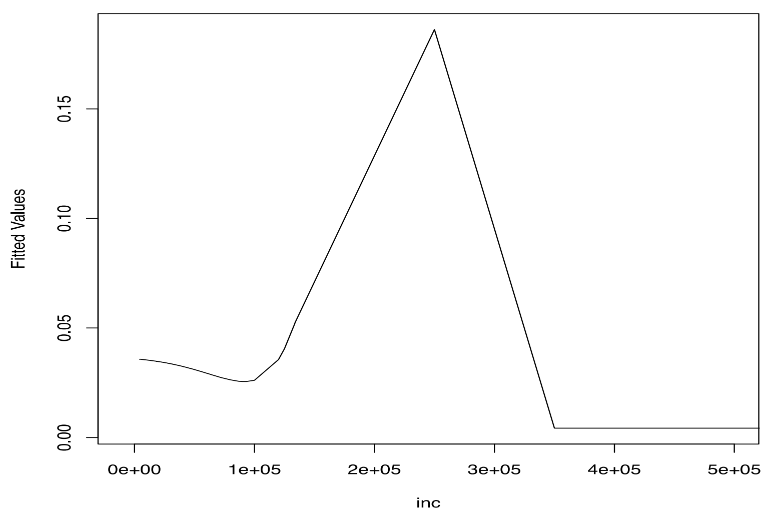
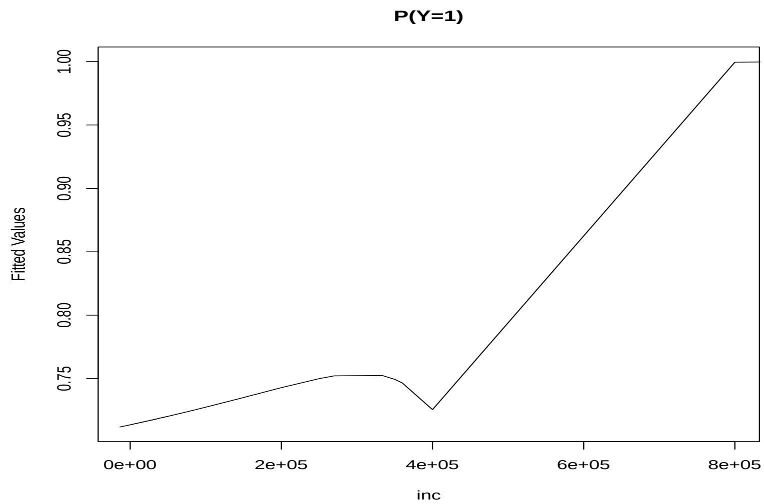
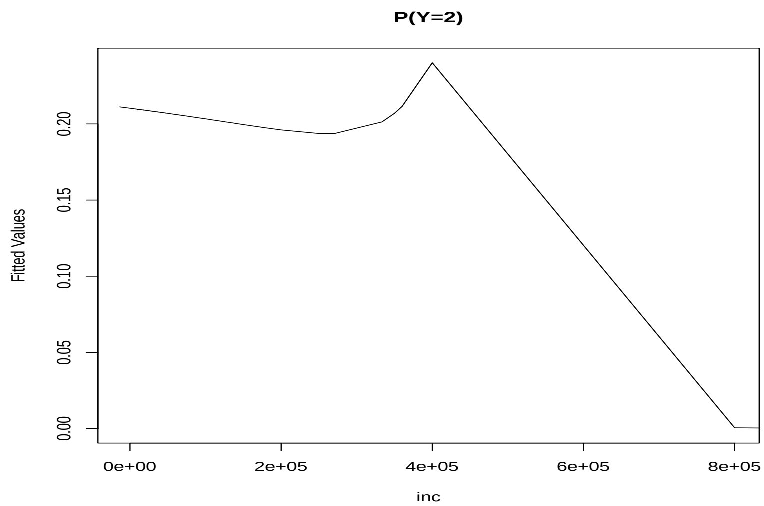
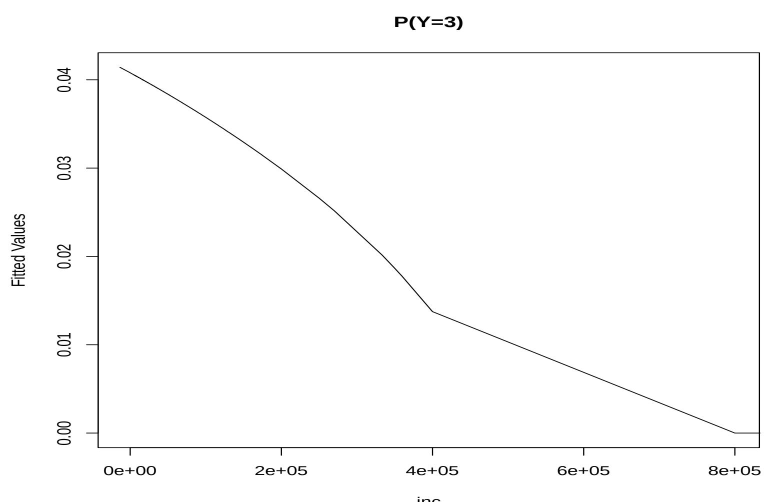



Figure 6 - $\hat{f}$ (No. of Any Medications$|X$, Used Any Medication $=$ YES) Versus Family-Adjusted Income


P(Y=1)
Fitted Values
0.75
0.80
0.85
0.90
0.95
1.00
0e+00
2e+05
4e+05
6e+05
8e+05
inc


P(Y=2)
Fitted Values
0.00
0.05
0.10
0.15
0.20
0e+00
2e+05
4e+05
6e+05
8e+05
inc


P(Y=3)
Fitted Values
0.00
0.01
0.02
0.03
0.04
0e+00
2e+05
4e+05
6e+05
8e+05
inc

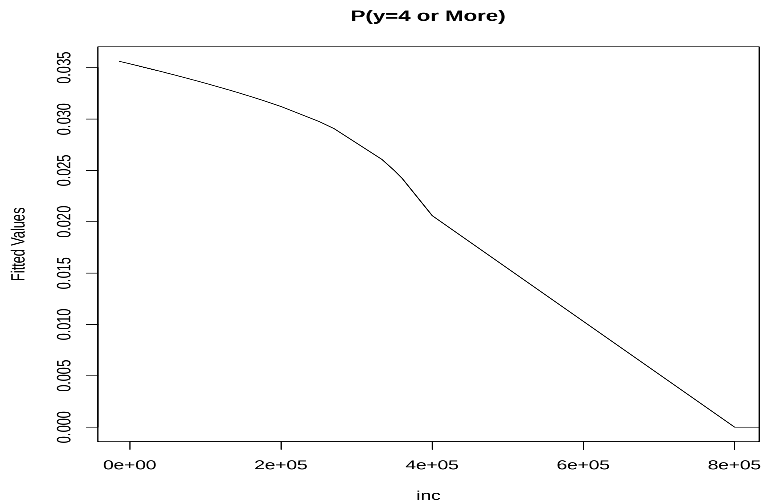



Figure 7 - $\hat{f}$ (No. of Antipsychotics $\geq 2|X$, Used Antipsychotic $=$ YES) Versus SPS

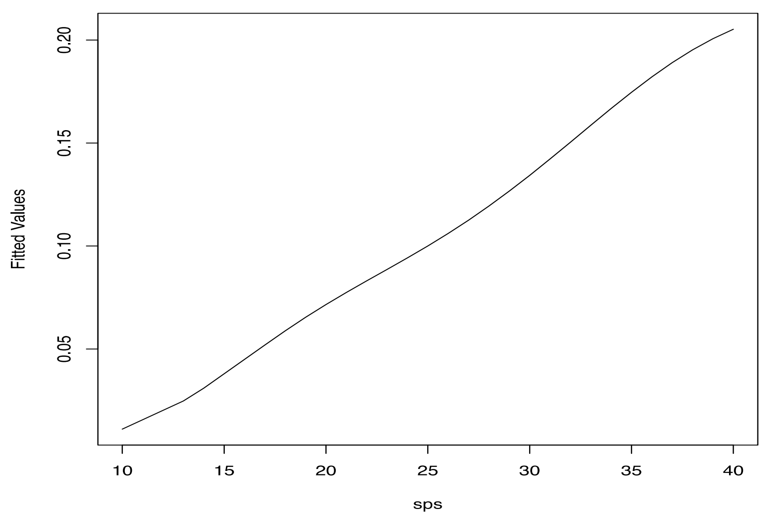
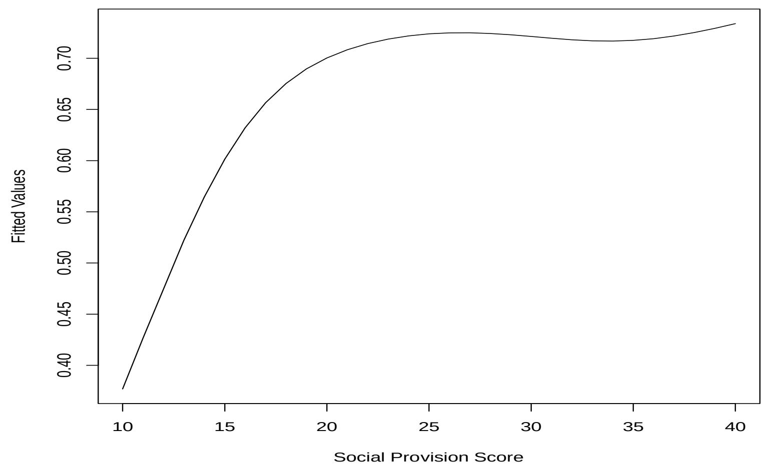
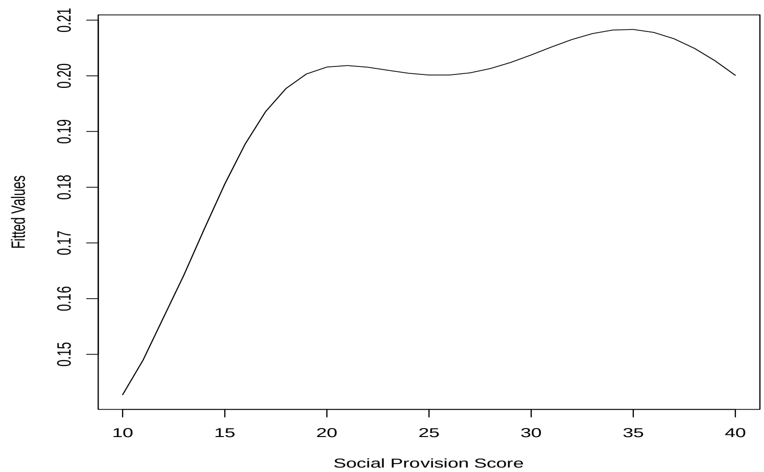



Figure 8 - $\hat{f}$ (No. of Any Medications$|X$, Used Any Medication $=$ YES) Versus SPS

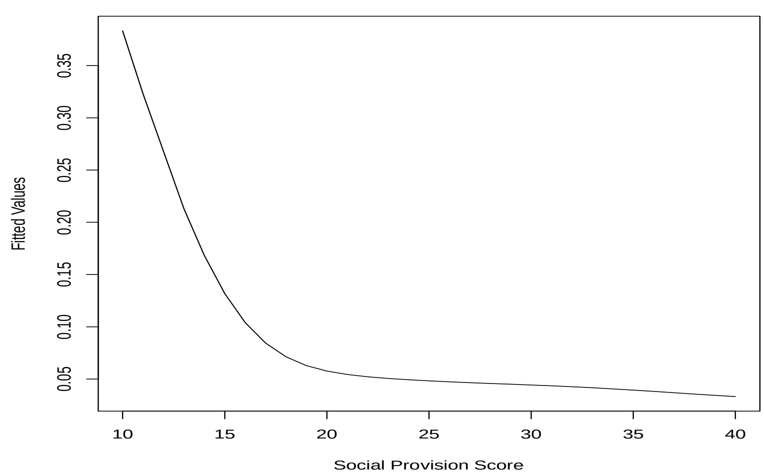
**P(Y=1)**


Fitted Values
0.40
0.45
0.50
0.55
0.60
0.65
0.70
10
15
20
25
30
35
40
Social Provision Score

**P(Y=2)**


Fitted Values
0.15
0.16
0.17
0.18
0.19
0.20
0.21
10
15
20
25
30
35
40
Social Provision Score

**P(Y=3)**


Fitted Values
0.05
0.10
0.15
0.20
0.25
0.30
0.35
10
15
20
25
30
35
40
Social Provision Score

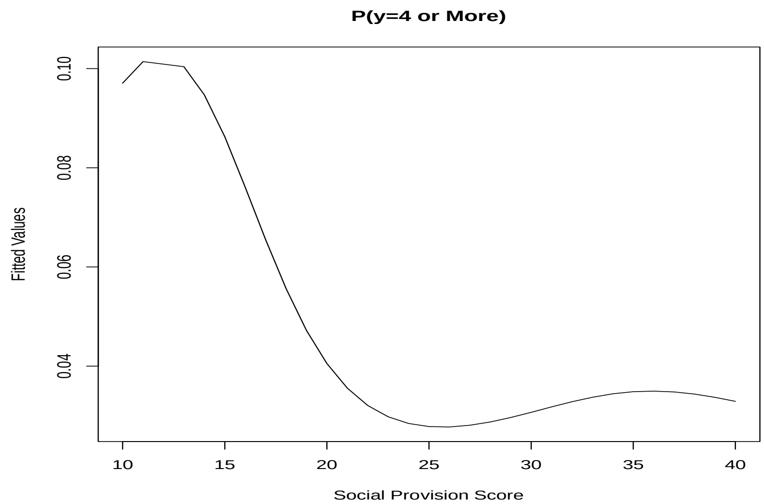
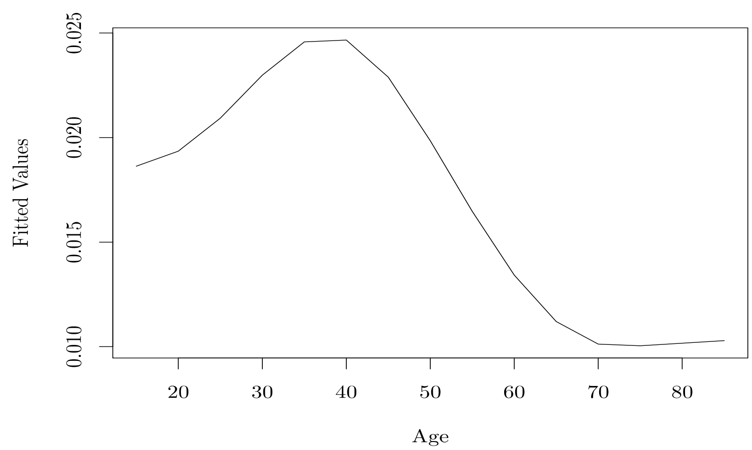
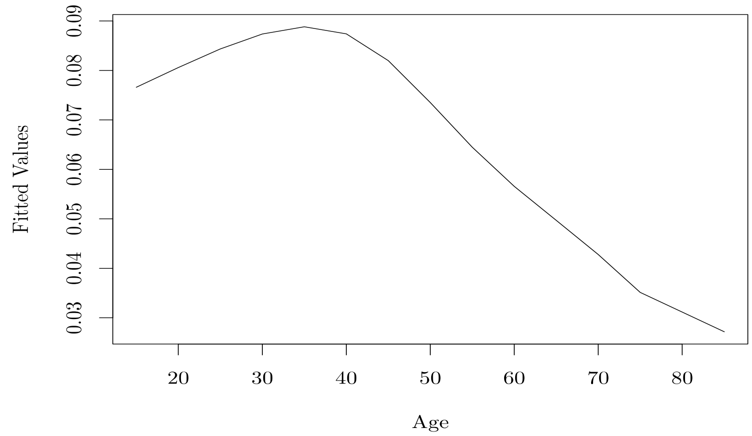



Figure 9 - $\hat{f}$ (Visited Professional $=$ YES$|X$) Versus Age

(a) Psychiatrist




(b) GP




(c) Psychologist

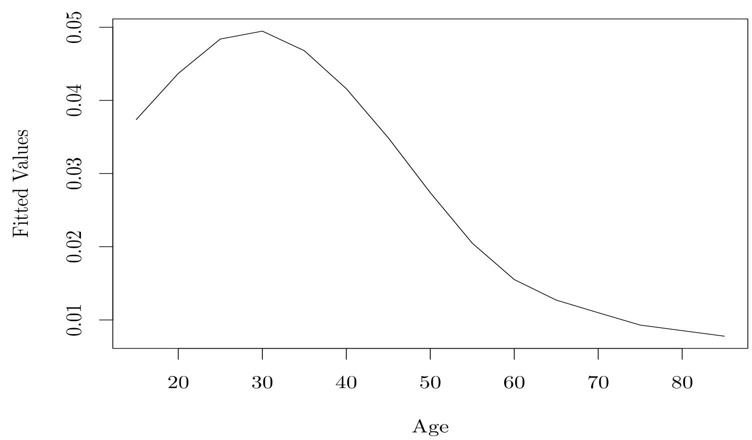
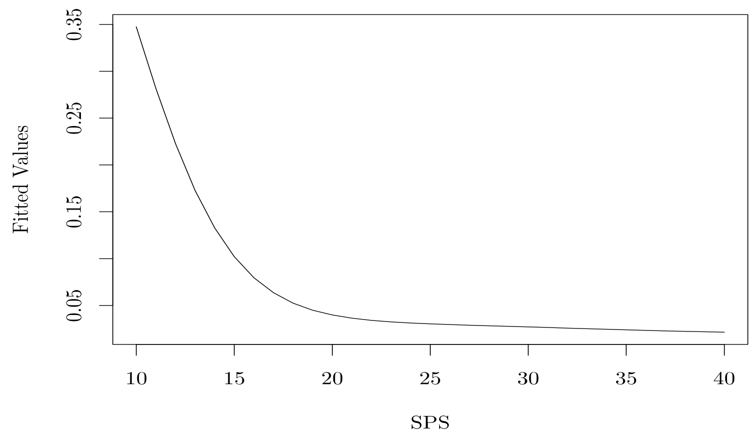
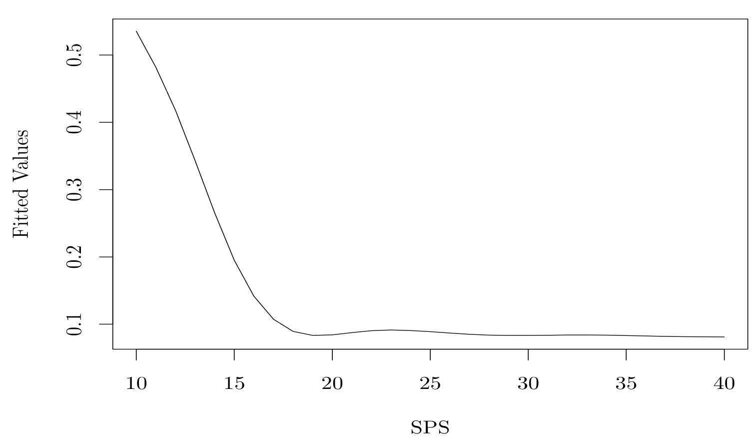



Figure 10 - $\hat{f}$ (Visited Professional $=$ YES$|X$) Versus SPS

(a) Psychiatrist


Fitted Values
0.05
0.15
0.25
0.35
10
15
20
25
30
35
40
SPS

(b) GP


Fitted Values
0.1
0.2
0.3
0.4
0.5
10
15
20
25
30
35
40
SPS