Estimating Local Prevalence of Mental Health Problems

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1 Introduction

Provision of mental health services is in a state of flux as the Patient Protection and Affordable Care Act affects provision and cost of medical care and state policymakers grapple with difficult trade-offs between budget balance and provision of public medical care. Mental health care provision is actually a relatively small part of the total cost of medical care provision. For example, based on an analysis of other studies, Mark et al. (2003) reports that between 9.3% and 13% of all Medicaid dollars are spent on behavioral health services. Figure 1 displays changes from 1986 - 2006 in the proportion of state-financed medical care that is for mental health care in Virginia (VA DMAS, 2006).[1] One can see the change in service provision from state psychiatric facilities to outpatient care. The total proportion has remained relatively constant at approximately 20% even as total expenditures increase by a factor of 7.72.[2] For many people struggling with mental health issues, these services are of critical importance. Kessler et al. (2001) estimates that more than 25% of U.S. adults had a mental illness in the previous year, with 7% having major depressive disorder and 18% having anxiety disorders.

An important issue to address in planning for mental health care provision is to be able to estimate the demand for such services, and usually it is important to estimate demand at a local level.[3] There is significant variation in how states organize their mental health systems. There are 19 states that provide services through city/county single or multi-jurisdictional governments (e.g., New York, North Carolina, Pennsylvania, Virginia), 38 that provide funding

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[1] Later, in Section 5.5, I perform an empirical exercise using data from central Virginia.

[2] Lutterman (2011) shows similar results across the United States.

[3] Regier et al. (1998) argues that diagnostic counts by themselves are not that useful for mental health planning purposes.

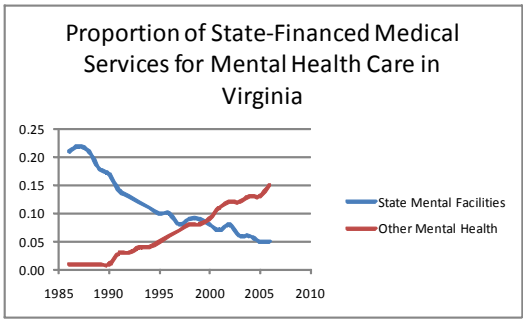

Figure 1: Proportion of State-Financed Medical Services for Mental Health Care in Virginia

to community-based agencies (e.g., Georgia, Illinois, New Jersey), and 12 that provide services directly through the state government (e.g., Louisiana, New York, Ohio)[4] (NASMHPD Research Institute, 2010). However, in all cases, services are provided at a local level. For example, in Virginia, there are 40 community service boards (CSB), some sharing boundaries with a specific county or city and others aggregating multiple counties. The largest CSB is Fairfax-Falls Church CSB with approximately 1.0 million people in its catchment area, and the smallest is Dickenson County Behavioral Health Services with approximately 16.2 thousand people in its catchment area.

Over the last two decades, a literature has developed to provide estimates of local measures of importance (see Section 2). The basic idea in this literature is to estimate models of the effect of a set of observable explanatory variables on relevant outcomes using a national dataset and then predict outcomes locally using information on the local joint distribution of the explanatory variables. In this paper, I contribute to this literature in a number of important ways:

1. I improve the existing methodology by a) allowing for non-perfect intersection of explanatory variables observable in a national survey and explanatory variables available locally; b) allowing for and appropriately modelling many types of explanatory variables (e.g., continuous, binary, ordered discrete, polychotomous discrete, censored) all in one encompassing framework; and c) providing comparisons across different approaches to deal with multiple outcomes associated with different diagnoses.

2. I document large differences in outcomes across different surveys. In particular, there are order-of-magnitude differences between estimates based on survey methods used in the National Health Interview Surveys until the mid-1990s and more recent surveys, and there are large differences in estimated prevalence of large-category diagnoses (such as substance abuse and depression) across all surveys. Part of the problem is that there is no

[4] Note that there is some overlap (e.g., New York).

such object as a "gold standard" measure of mental health. For example, while Kessler et al. (2005) provides strong evidence that the National Comorbidity Study (NCS) provide results similar to the earlier Epidemiologic Catchment Area (ECA) Study and to clinical results, Kessler et al. (2004) acknowledges that there is no "gold standard" to compare to the NCS, and Grant et al. (2007) argues that the NCS underestimates substance dependency because of the nature of the screening questions. While I have nothing to contribute on the "best" or even better ways to measure mental health, I document important variation in the methods used over the last two decades.

3. I document and discuss the existence of empirically important geography-specific unobserved heterogeneity. The existence of such unobserved heterogeneity makes it difficult and, given present data availability, maybe impossible to construct precise estimates of local prevalence.

4. Instead of focusing on just an estimate of the number of people with mental health problems, I focus on the distribution of the probability that a local individual has a mental health problem. The distribution provides extra, useful information and still provides an estimate of the number of individuals with mental health problems.

5. I provide an example of how to use estimates for planning with a specific application to provision of public mental health services in central Virginia.

The structure of the remainder of this paper is as follows: Section 2 provides a review of the existing literature. Section 3 describes the proposed methodology. Section 4 describes the data used in the analysis. I use three different national surveys to measure the effect of explanatory variables on mental health outcomes, one dataset with local information, and one more providing estimates of location-specific unobserved effects. I provide empirical results in Section 5 for each of the three data sources of mental health outcomes and compare alternative models as well. In Section 6, I apply the empirical results from two of three datasets to public mental health care planning in central Virginia. The paper ends with conclusions.

2 Literature Review

The idea of using large national surveys to estimate local distributions of interest has been used in development economics by Ghosh and Rao (1994), Rao (1999), Alderman et al. (2002), and Elbers, Lanjouw, and Lanjouw (2003); in health applications by Malec et al. (1997), Twigg, Moon, and Jones (2000), Legler et al. (2002), Mendez-Luck et al. (2007), Choy et al. (2008), and Congdon (2009); in mental health applications by Kessler et al. (1998), Messer et al. (2004) and Congdon (2006); and for allocation of resources at local levels by Citro and Kalton (2000). Much of the literature focuses on continuous outcome

measures such as income, but there is a growing literature where the outcome is a qualitative or discrete variable (see, for example, Ghosh et al., 1998). Though much of the literature uses Bayesian methods (see, for example, Ghosh and Rao,1994; Malec et al.,1997), Jarjoura et al. (1993), Elbers, Lanjouw, and Lanjouw (2003), and Konrad et al. (2009) suggest building a model of the outcome variable, estimating the model parameters using classical methods, and then using the estimated relationship to project locally. I follow a similar approach to Elbers, Lanjouw, and Lanjouw (2003) and Konrad et al. (2009)[5] but allow for a possible imperfect match of variables available nationally and locally using methodology developed in Lavy, Palumbo, and Stern (1998). This addition allows one to use critical variables available nationally even if they are not available locally.

The methodology discussed above ignores any unobserved geographical heterogeneity. To the degree that such heterogeneity is important, the methodology may have significant consistency issues. This point is forcefully made by Tarozzi and Deaton (2008). It creates synthetic local data sets from a national data set and show that, while there is valuable information in the procedure, the nominal precision of the estimates is overestimated. I use a different approach here using a national survey with some geographic information and measure the variation in community fixed effects.

Part of the cause of the discrepancy across different surveys may be due to the nature of the questioning. The NCS performs a structured interview that allows for identification of people with mental health problems, even if the problems are mild. In fact, Kessler et al. (2005) reports that, among those who are identified as having a mental health problem, 22.3% were classified as severe, 37.3% as moderate, and 40.4% as mild. Narrow et al. (2002) gets much lower prevalence estimates when it limits prevalence to those who are "clinically relevant." Meanwhile, the NHIS asks respondents to self-identify themselves as having a mental health problem. It is quite possible that those with mild problems fail to do so.

3 Methodology

The basic idea in this paper is to estimate discrete choice models of mental health problem probabilities using national data, simulate a random sample of local individuals, and use the random sample to simulate prevalence. In some sense, this is similar to Congdon (2006). But I generalize by allowing for polychotomous discrete measures of mental health problems, by allowing for the possibility of needing to impute some important explanatory variables in local data, and by using classical econometric methods instead of Bayesian

[5] Konrad et al. (2009) goes a few steps further in constructing estimates of discrepancies between supply and demand for mental health services. In particular, it estimates individual demand for mental health services conditional on observed demographic and mental health characteristics to complete the task of estimating demand for services. Then, Ellis et al. (2009) estimates supply of mental health providers disaggregated by type of provider and geography.

methods. It is also similar to Kessler et al. (1998) except that I use only national surveys to estimate my models while Kessler et al. (1998) merges NCS data with census data at very small levels of geography. Also, I estimate equations for different mental health conditions both separately and together, and Kessler et al. (1998) estimates only one equation for a binary SMI indicator. I divide up the discussion into the three components discussed above in the three following subsections.

3.1 Estimating Mental Health Problem Probabilities

Consider three different models of having a mental health probability. In the first model, let y_i^* be the latent propensity for individual i to have a mental health problem of any type, and assume that

$$y_i^* = X_i\beta + e_i \tag{1}$$

where X_i is a vector of demographic and physical health characteristics of i and $e_i \sim iidN(0,1)$. Let $y_i = 1(y_i^* > 0)$. In the data, I observe $\{y_i, X_i\}_{i=1}^n$ for a national random sample of n observations. This is the standard specification for a probit model.

For the second and third model, let y_{ij}^* be the latent propensity for i to have a mental health problem of type j, $j = 1, 2, .., J$, and assume that

$$y_{ij}^* = X_i\alpha_j + u_{ij}. \tag{2}$$

As before, let $y_{ij} = 1\left(y_{ij}^* > 0\right)$. If it is assumed that $u_{ij} \sim iidN(0,1)$, then one has a set of J independent probit models. Alternatively, one can define $u_i = (u_{i1}, u_{i2}, .., u_{iJ})'$ as the vector of errors and assume that

$$u_i \sim iidN(0,\Omega). \tag{3}$$

Given the identification restriction on Ω that all of the diagonal elements must be restricted to one, this is a multivariate probit model and can be estimated using maximum simulated likelihood.[6]

3.2 Simulating Missing Values

One also must have access to a local data set $\{Z_{1i}, Q_i\}_{i=1}^m$ where Z_{1i} is a vector of demographic and physical health characteristics for individual i with corresponding elements in X and Q_i is a vector of variables also available in the national data but not part of X. Define $Z_i = (Z_{1i}, Q_i, Z_{2i})$ where the elements of Z_{2i} are equal to the corresponding elements of X not available in the local data and Z_{2i} is not observed.[7] The goal is to simulate Z_{2i}[8] given (Z_{1i}, Q_i) and

[6] See Borsch-Supan and Hajivassiliou (1993) or Stern (1997) for a discussion.

[7] Kessler et al. (1998) does not need to simulate any missing values because they limit the set of explanatory variables to a small set available in Census data.

[8] There may be some individual observations in the local data set with missing values. For such observations, one can treat the individual missing variables as part of Z_{2i}.

then use the simulated Z_i along with the estimates of β in equation (1) and/or α in equation (2) to simulate local mental health problem prevalence rates. Decompose X_i into (X_{i1}, X_{i2}) where X_1 corresponds to Z_1 and X_2 corresponds to Z_2.

Following and generalizing Lavy, Palumbo, and Stern (1998) (LPS), define X_{1i}^* as a set of latent variables associated with X_{i1}. Let X_{1ik} be the kth element of X_{1i}. Given the available data, there are five[9] relevant cases:[10]

1. If X_{1ik} is continuous (e.g., age), then define $X_{1ik}^* = X_{1ik}$.
2. If X_{1ik} is binary discrete (e.g., female), then define $X_{1ik}^* : X_{1ik} = 1\left(X_{1ik}^* > 0\right)$.
3. If X_{1ik} is an ordered discrete variable (e.g., poor health, fair health, good health, an excluded category of excellent health), then define $X_{1ik}^* : X_{i1k} = h1\left(\tau_h < X_{1ik}^* \leq \tau_{h+1}\right)$ where τ is a vector of (estimable) thresholds.
4. If X_{1ik} is a censored continuous variable (e.g., censored family income), then define $X_{1ik}^* : X_{1ik} = \min\left[X_{1ik}^*, c\right]$.
5. If X_{1ik} is a polychotomous discrete choice variable (e.g., white, black, other race), then define $\left(X_{1ik}^*, X_{i1k+1}^*, .., X_{i1k+H-1}^*\right)$ where H is the number of discrete choices such that $X_{1ik} = \chi$ iff $X_{1ik+\chi}^* \geq X_{1ik+h}^* \forall h = 0, 1, .., H$ and $X_{1ik} = H$ iff $X_{1ik+h}^* < 0 \forall h = 0, 1, .., H$.

Define (Q_i^*, X_{2i}^*) similarly.

Next, define $X_i^* = (X_{1i}^*, Q_i^*, X_{2i}^*)$, and assume that $X_i^* \sim iidN\left(\mu, \Psi\right)$. LPS shows that the joint normality assumption is relatively innocuous. Decompose

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_Q \\ \mu_2 \end{pmatrix}, \quad \Psi = \begin{pmatrix} \Psi_{11} & \Psi_{1Q} & \Psi_{12} \\ \Psi_{Q1} & \Psi_{QQ} & \Psi_{Q2} \\ \Psi_{21} & \Psi_{2Q} & \Psi_{22} \end{pmatrix}$$

into blocks corresponding to the decomposition of X_i^*. The joint normality assumption implies that

$$X_{2i}^* \mid X_{1i}^*, Q_i^* \sim iidN\left[\mu_2 - A_{22}^{-1}\begin{pmatrix} A_{12} & A_{Q2} \end{pmatrix}\begin{pmatrix} X_{1i}^* - \mu_1 \\ Q_i^* - \mu_Q \end{pmatrix}, A_{22}^{-1}\right]$$

where $A = \Psi^{-1}$ and A is decomposed similarly to Ψ. Thus, it is straightforward to simulate $X_{2i}^* \mid X_{1i}^*, Q_i^*$ given estimates of (μ, Ψ). With a simulated value of X_{2i}^*, it is straightforward to simulate X_{2i} using the inverse of the rules defining X_{2i}^* using the GHK algorithm (see, for example, Geweke 1991).

Still following and generalizing LPS, estimate (μ, Ψ) in three steps. In the first step, estimate means and variances. In general, this involves solving moment conditions for the first two moments of the data. Details for type (1)-(3) variables are provided in LPS. Censored variable moments are also straightforward to estimate. The only complication occurs for polychotomous discrete

[9] LPS allows for cases (1), (2), and (3) but not (4) and (5).

[10] See, for example, Maddala (1983) for a discussion of each of these cases.

choice variables. In this case, for a general model, the covariance matrix of $\left(X_{1ik}^{*}, X_{i1k+1}^{*}, .., X_{i1k+H-1}^{*}\right)$ is identified because there are observable covariates that allow for identification. When there are no observable covariates as is true in this exercise, the covariance matrix is not identified. Thus, set it equal to the identity matrix with no loss in generality.

The second step involves matching theoretical covariance terms and corresponding sample covariances. In general, this is straightforward but involves numerical optimization. Details involving variable types (1)-(3) are provided in LPS, and the other cases follow analogously.

The last step involves insuring that the estimated covariance matrix $\widehat{\Psi}$ is positive definite. Following LPS, let λ be the set of eigenvalues of $\widehat{\Psi}$ and E be the associated matrix of eigenvectors. Define $\widehat{\lambda_k} = \max\left(\lambda_k, \kappa\right)$ for some chosen $\kappa > 0$. Then $\widetilde{\Psi} = Ediag\left(\widehat{\lambda}\right)E'$ is the closest positive definite matrix to $\widehat{\Psi}$ in a relevant metric and, since each of the elements of $\widehat{\Psi}$ is consistent, $plim\widetilde{\Psi} = \Psi$.

3.3 Simulating Prevalence

Once one has a method of simulating $X_{2i} \mid X_{1i}^{*}, Q_i^{*}$, one can apply the same methodology to simulate $Z_{2i} \mid Z_{1i}^{*}, Q_i^{*}$ using the local data and the estimates of (μ, Ψ) from the national data. Given a simulated value of Z_{2i}, one can simulate $p_j\left(Z_i\right) = \Pr\left[y_{ij} = 1 \mid Z_i\right]$ locally using the parameter estimates of β or α from the national sample. Furthermore, one can use the simulated values of $p_j\left(Z_i\right)$ to plot the distribution of mental health risk in the community. In particular, Elbers et al. (2007) shows that it is important to target programs not just using local prevalence (in their case, of poverty) but to also consider heterogeneity within a local area. It also quantifies the value of having more data on individuals within a local area. My methodology allows one to target programs based on observed heterogeneity and to quantify the value of gaining more information locally, either on the outcome of interest directly or on the indicators included in national data but not available locally.

3.4 Simulating Measures of Errors of Estimates

The methodology above provides estimates of a number of different objects including mean prevalence, the marginal distribution of prevalence for a particular condition, and the joint distribution of prevalence of a number of conditions. Given the nonlinearity and complexity of the methodology, the easiest and most robust method for estimating measures of error is parametric bootstrapping. It is straightforward to use Monte Carlo methods to simulate any measure of errors as long as the measure has finite moments. In this case, since the objects of interest involve probabilities, which are bounded, there are no issues associated with non-existing moments.

The big issue is what measure of errors to use. For the local mean prevalence, an obvious measure of error is the standard error of the estimated mean. For any marginal distribution, one can report confidence intervals for quantiles of

the estimated distribution. While there are many other ways to summarize marginal or joint distributions, quantiles seems an appropriate approach for this application. One can simulate confidence intervals easily using draws of parameters from their asymptotic distribution.

4 Data

I use five different data sets in this analysis. I use the National Health Interview Survey (1995) (NHIS), the National Survey of Alcohol, Drug and Mental Health Problems (2000-2001) (NSADMHP), and the National Comorbidity Survey-Replication (2001) (NCS-R) to estimate probit models of mental health problems as discussed in Section 3.1.[11] Throughout the paper, I focus on one-year prevalence rates. Mostly I focus on one-year prevalence rates because they are more relevant for determining need for resources. However, there also might be some data precision issues associated with lifetime prevalence.[12] I also use the NHIS to estimate the joint distribution of latent variables associated with explanatory variables as discussed in Section 3.2. I use the Bureau of Census Public Use Microdata Sample (PUMS) for the Charlottesville metropolitan statistical area (MSA) (2000) to simulate local prevalence rates as described in Section 3.3. Finally, I use the Community Tracking Survey (2003) to learn more about other characteristics of prevalence rate estimation reported in Section 5. In the remainder of this section, I discuss some of the details of each of the utilized data sets.

4.1 National Health Interview Survey

The National Health Interview Survey (NHIS) is a repeated cross-section, administered by the National Center for Health Statistics, going back to 1970. The NHIS includes a moderately-sized set of demographic and economic questions and an extensive set of physical health questions. Also, from early years up until 1995, the NHIS asked a series of mental health diagnosis questions. Individuals were asked a series of questions which were then used to construct mental health problem measures.[13] After 1995, the structure of the mental health questions completely changed as described in Kessler et al. (2002), making it not useful for this analysis.

The NHIS has 95091 observations. I exclude 40337 because of reasons described in Table 1, leaving a sample of 54754. The major selection criterion,

[11] Other potential sources of data are a) the National Survey on Drug Use and Health (SAMHSA, 2003), emphasizing substance abuse; and b) the Behavioral Risk Factor Surveillance System (See Moriarty et al., 2009).

[12] Weissmann et al. (1991) finds that lifetime prevalence rates for affective disorders decline with age. Helzer, Burnam, and McEvoy (1991) finds similar results for alcohol abuse. This age effect on *lifetime* prevalence is mechanically impossible as a true age effect; however it could be a cohort effect. See, for example, Grella (2009) for a thoughtful discussion of cohort effects with respect to substance abuse.

[13] The variables used are listed in Section 8.1.

Table 1: Missing Data Analysis for NHIS			
Variable	Selection Criteria	# Excluded	Cumulative
Age	Age >18	28730	28730
Race	not missing	919	29649
Hispanic	not missing	102	29751
Marital Status	not missing	120	29871
Veteran Status	not missing	873	30744
Education	not missing	383	31127
Family Income	not missing	8857	39984
Subjective Health	not missing	353	40337

Table 2A: NHIS Dependent Variable Proportions	
Diagnosis	Proportion
Anxiety	5.97%
Schizophrenia	0.22%
Paranoia	0.29%
Bipolar	0.52%
Depression	3.49%
Personality Disorder	1.51%
Dementia	0.20%
Substance Abuse	0.71%
Other Mental Health Problem	3.89%

Table 2B: NHIS Density of Number of Co-occurring Mental Health Problems	
# Problems	Density
0	89.97%
1	6.17%
2	2.16%
3	0.96%
4 or more	0.74%

causing 71% of the excluded observations, is the condition that one must be at least 19 years old. The remaining exclusions occur because of missing information.

The moments of the data for the selected sample are shown in Tables 2A, 2B, and 2C. Tables 2A and 2B provide information about the mental health problem variables. One sees that anxiety is the most commonly reported mental health problem,[14] followed by depression and other mental health problems (mainly phobias). Table 2B provides information on the frequency of co-occurring mental health problems. Based on the NHIS, 10.0% of the population has a mental health problem. The other surveys used in this work will have quite different proportions (see below). Among those who have at least one mental health problem, 39.5% have more than one problem.

Table 2C provides information on the moments of the explanatory variables used from the NHIS. I include some demographic variables, economic status variables, and health variables. There are four categories for marital status: married, divorced, widowed, and never married; and never married is the base status. There are three levels of education: no high school diploma, high school diploma but no college degree, and college degree. I disaggregate the US into four regions and distinguish between those living in metro areas (In MSA) and

[14] This may occur because the question used to identify anxiety is "Frequently Depressed or Anxious," thus probably including some respondents with depression as suffering from anxiety.

Table 2C: NHIS Explanatory Variable Moments					
Variable	Mean	Std Dev	Variable	Mean	Std Dev
Female	0.53	0.50	Northeast	0.20	0.40
Age/100	0.45	0.17	Midwest	0.23	0.42
Black	0.11	0.32	South	0.35	0.48
Other Race	0.08	0.27	In MSA	0.80	0.40
Hispanic	0.16	0.36	Height/Weight	2.46	0.50
Married	0.66	0.47	Health Fair	0.09	0.29
Divorced	0.10	0.30	Health Poor	0.04	0.19
Widowed	0.07	0.25	Has Medical Condition	0.13	0.34
Veteran	0.15	0.35	Has ADL Problem	0.02	0.13
HS Diploma	0.80	0.40	Has IADL Problem	0.07	0.25
College Degree	0.22	0.41	Has Functional Limitations	0.14	0.34
Family Income ($1K)	31.88	15.65	Work Disability Limits Work	0.04	0.21
Family Income > 50	0.27	0.45	Work Disability Prevents Work	0.06	0.24
			Has Mobility Disability	0.04	0.20

Notes:
1.The base status for marital status is never married.
2.Family Income is censored at 50.

those not in metro areas. There are three levels of reported health:[15] *health poor*, *health fair*, and *health better than fair*[16] with the third category the base. Also, I observe whether one has a chronic medical condition, activities of daily living (ADL) and/or instrumental activities of daily living (IADL) problems, and any functional limitations.[17] Using the notation from Section 3.2, I define X to include all of the explanatory variables, along with a constant, $(age/100)$, $(age/100)^2$, and $(age/100)^3$, excluding the two work disability variables and the mobility disability variable, and Q to consist of the two work disability variables and the mobility disability variable.

4.2 National Comorbidity Survey-R

The NCS-R is a nationally representative follow-up of the original NCS from 1992, a pioneering survey on psychiatric epidemiology.[18] It builds on and expands the set of questions from the original survey. It was managed by the Survey Research Center at the University of Michigan. The core questionnaire was based largely on the World Health Organization's (WHO) expanded version of the Composite International Diagnostic Interview (CIDI). The CIDI was designed to produce International Classification of Diseases (ICD) diagnoses but

[15] Variable names are written in a different font to distinguish them from the English usage of the same word.

[16] *Health better than fair* aggregates *health good* and *health excellent*.

[17] I classify someone as having a functional limitiation if they answer affirmatively to being limited in any one of the following ways: a) lifting; b) climbing steps; c) walking; d) standing; e) bending; f) reaching; g) using fingers; or h) writing.

[18] The NCS-R is part of a consortium of surveys, the Collaborative Psychiatric Epidemiology Surveys (CPES). The CPES merges data from the NCS-R, the National Survey of American Life, and the National Latino and Asian American Study. See Alegria et al. (2006a, 2006b), Heeringa et al. (2006), Jackson et al. (2006a, 2006b), and Pennell et al. (2006) for more detail.

Table 3: Concordance of ICD-9 and DSM-IV Diagnoses in NCS-R

	Neither	ICD-9 Only	DSM-IV Only	Both	Pr[Either]	Kappa
Depression/ Dsythymia	8290	13	307	499	0.090	0.739
Anxiety Disorders	8682	40	100	287	0.047	0.796
Phobia	7296	485	217	1111	0.199	0.714
Bipolar Disorder	8196	12	680	221	0.100	0.364
Panic Disorders	7931	6	217	955	0.129	0.882
Personality Disorders	8657	17	389	46	0.050	0.175
Alcohol Abuse	8887	4	0	218	0.024	0.991
Drug Abuse	9011	1	0	97	0.011	0.995
Eating Disorder	9021	0	76	12	0.010	0.238

could also be used to construct Diagnostic and Statistical Manual of Mental Disorders (DSM) diagnoses.[19] The NCS-R includes a moderately-sized set of demographic, health, and economic questions with significant but not perfect overlap with the NHIS.

The NCS-R has 9283 observations. I exclude 174 observations, almost all because *age* is not in the desired range. I focus only on whether the respondent has a mental health problem rather than disaggregating by diagnosis because of the apparent lack of concordance between ICD and DSM diagnoses seen in Table 3 and Section 4.6. Rounsaville (2002) points out that relatively small changes in diagnosis criteria between ICD-10 and DSM-IV lead to large variation in prevalence rates for substance abuse. Andrews and Slade (2002) reports estimated prevalence rates using ICD-10 and DSM-IV for generalized anxiety disorder using an Australian survey with 10641 observations. It finds a κ-value of 0.39. However even though κ is low, the reported prevalence rates for ICD-10 and DSM-IV are not that different (3.0% and 2.6% respectively). Using somewhat different methodology, Hiller et al. (1993) finds similar types of results for ICD-10 and DSM-III-R with respect to affective and psychotic disorders. For this research, I use DSM diagnoses to encourage concordance with the NSADMHP (see Section 4.3). Among the 9109 observations, 29.0% report having a mental health problem.

The moments of the explanatory variables are shown in Table 4. I include some demographic variables, economic status variables, and health variables. There are three categories for marital status: married, divorced/widowed, and never married; and never married is the base status. *Education*, *health*, and *region* are constructed the same as for the NHIS. Also, I observe whether one has a chronic medical condition, ADL and/or IADL problems, and any functional limitations.[20] Because the prevalence of IADLs is so low, I do not use it in the

[19] The ICD is published by the WHO and used internationally to classify diseases including mental health disorders. The DSM is published by the American Psychiatric Association and prefered over the ICD by psychiatrists, especially in the U.S., in order to diagnose patients with mental disorders. See Andrews, Slade, and Peters (1999) or American Psychological Association (2009) for more information.

[20] I classify someone as having a functional limitiation if they answer affirmatively to any one of the three questions: a) Have you been limited in past 3 months due to a health problem

Table 4: NCS-R Explanatory Variable Moments

Variable	Mean	Std Dev	Variable	Mean	Std Dev
			Attends Religious Services		
Female	0.56	0.50	Frequently	0.34	0.47
Age/100	0.45	0.17	Religion is Important	0.59	0.49
Black	0.13	0.34	Northeast	0.18	0.39
Other Race	0.05	0.22	Midwest	0.27	0.44
Hispanic	0.09	0.29	South	0.34	0.48
Married	0.58	0.49	Health Fair	0.03	0.17
Divorced/Widowed	0.22	0.42	Health Poor	0.01	0.08
HS Diploma	0.86	0.35	Has Medical Condition	0.32	0.47
College Degree	0.43	0.49	Has ADL Problem	0.01	0.09
Family Income ($1K)	22.57	21.96	Has IADL Problem	0.00	0.03
Family Income > 50	0.29	0.46	Has Functional Limitations	0.23	0.42
Employed	0.41	0.49	Work Disability Limits Work	0.04	0.19
Receives Public Assistance	0.02	0.15	Work Disability Prevents Work	0.01	0.11
Citizen	0.98	0.14	Has Mobility Disability	0.13	0.34
Immigrant	0.06	0.23			

Notes:
1.The base status for marital status is never married.
2.Family Income is censored at 50.
3.Conditions included in "has medical condition" are arthritis, chronic back problems, chronic pain, heart problems, asthma, COPD, diabetes, ulcer, epilepsy, cancer, and collitis.

estimation. There are two measures of religiosity and two variables measuring connectedness to US society.[21] Unfortunately, there is no measure of veteran status even though veteran status has such a large effect on mental health problems. Compared to data from the NHIS, the NCS-R under-represents Hispanics, married people, people in poor and fair health, and people for whom a work disability prevents work, and it over-represents people with college degrees,[22] people with functional limitations, and people with mobility disabilities.

Using the notation from Section 3.2, define X to include all of the explanatory variables (except for *IADL problems*), along with a third order set of orthogonal polynomials in *age*, excluding the two work disability variables and the mobility disability variable, and Q to consist of the two work disability variables and the mobility disability variable.

4.3 National Survey of Alcohol, Drug, and Mental Health Problems

The NSADMHP is a short panel of individuals from the Community Tracking Survey (CTS) (see Section 4.5) and augmented with a supplemental sample. Based on information from CTS, individuals were oversampled if they were low-income respondents, individuals who had used specialty mental health services in the preceding year, or individuals who had reported high psychological distress. The oversampling associated with mental health variables could cause significant inference problems for estimates from this sample.

(Variable SC10_1H); b) Do you have a physical disability (Variable SC10_4E); or c) Do you have a condition that substantially limits physical activity (Variable SC10_4F).

[21] See, for example, Alexandre and French (2001) for a discussion of the relationship between religiosity and mental health.

[22] The *college* variable is constructed as the union of four separate questions of highest grade attained. While there are a few cases where there are inconsistencies across these four measures, they are not the cause of the unusually high proportion of college graduates.

Table 5A: Mental Health Problems Prevalence in the NSADMHP		
Variable	Prevalence/Mean	Std Dev
Anxiety	0.046	
Depression	0.122	
Dysthymia	0.054	
Psychosis	0.017	
Panic (DSM)	0.071	
Panic (CIDI)	0.045	
Substance Abuse	0.069	
Any Mental Health Problem	0.236	
MCS-12	44.983	5.971
MHI-5	77.896	18.268

From an initial sample of 6659 observations, I exclude observations if *marital status*, *health*, *# dependents*, *employment status*, or *psychosis dummy* is missing or if the observation is not part of the original 60-site CTS sample. Only the last criterion results in a significant loss of observations (868). The resulting sample size is 5747.

In the NSADMHP, mental health diagnoses are imputed based on answers to survey questions mimicing those in popular mental health screening instruments. Table 5A displays the moments of the mental health variables.[23] Compared to the National Health Interview Survey (Table 2A), there is a comparable prevalence for anxiety, significantly more depression, and significantly more substance abuse. The reported prevalence rate for any mental health problem is over twice as high as in the NHIS (23.6% vs 10.0%).

For panic disorders, the NSADMHP has two measures: one based on DSM-III criteria, and the other based on CIDI. *Panic* (DSM) is more prevalent, and, in fact, all those diagnosed with panic disorder using CIDI are also diagnosed using DSM-III.

The NSADMHP has two other continuous measures of mental health: *MCS-12* and *MHI-5*. The *MCS-12* is a commonly used measure of mental health status based on a limited number of screening questions. High scores correspond to good mental health. The mean score and standard deviation in the general US population is 50 and 10, respectively. *MHI-5* is another measure of mental health status based on 5 questions from a popular screening instrument (Mental Health Inventory). It is more closely tied to measures of anxiety, depression, loss of behavioral or emotional control, and psychological well-being. As with *MCS-12*, a high score implies better mental health.[24] Figure 2 displays the sample distribution of these two continuous measures conditional on whether one has one of the mental health diagnoses listed in Table 5A. One can see that the distributions of both *MCS-12* and *MHI-5* are sensitive to conditioning on having a mental health diagnosis, though *MCS-12* has relatively low predictive

[23] See Section 8.3 for a list of the NSADMHP question #s that define having a mental health problem.

[24] Kessler et al. (2002) suggests other similar measures based on DSM.

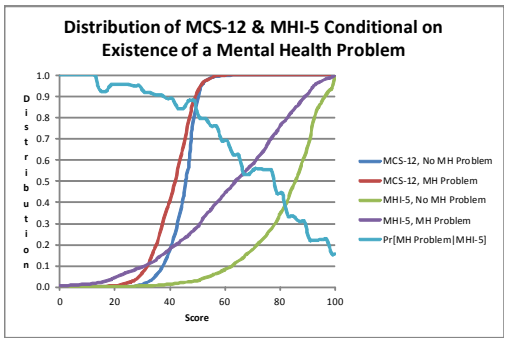

Figure 2: Distribution of MCS-12 & MHI-5 Conditional on Existence of a Mental Health Problem

power.[25] However, it is also clear that there is significant overlap of *MCS-12* and *MHI-5* scores among those who have and those who do have a mental health diagnosis. The declining curve in Figure 2 displays the estimated probability of having a mental health problem condition on one's *MHI-5* score.[26] It is clear that *MHI-5* provides significant predictive power for existence of mental health problems.

Table 5B provides moments for the explanatory variables in the NSADMHP. There is an unusually high proportion of women in the sample, almost surely caused by the sampling strategy. Also, compared to the NHIS moments in Table 2C, the NSADMHP under-represents Hispanics, grossly over-represents people with other conditions and functional limitations, and moderately over-represents people with poor and fair health.

4.4 PUMS Data for Charlottesville/ Albemarle County, VA

The PUMS is a cross-section representing a 1% sample from the 2000 Census for the Charlottesville VA MSA. The PUMS includes a moderately-sized list of demographic, economic, and health questions which are a subset of those available in NHIS. Of course, there are no mental health questions in PUMS; if there were, I could use them directly to estimate mental health problem prevalence.

PUMS has 7919 observations. The moments of the data for the selected sample are shown in Table 6A. Note that everyone in PUMS lives in the south and in an MSA. Also note that no one has a work disability that prevents work

[25] Gill et al. (2007) finds that *MCS-12* has good predictive power using Australian survey data. Fleishman and Lawrence (2003) suggests that, to some degree, *MCS-12*, scores may be contaminated by variation in demographic variables.

[26] The equivalent curve conditioning on *MCS-12* would be relatively flat given the small difference in *MCS-12* distributions.

Table 5B: NSADMHP Explanatory Variable Moments					
Variable	Mean	Std Dev	Variable	Mean	Std Dev
Female	0.63	0.48	Southeast	0.20	0.40
Age/100	0.49	0.16	Midwest	0.21	0.41
Black	0.12	0.32	Southwest	0.06	0.24
Other Race	0.03	0.17	Pacific	0.14	0.24
Hispanic	0.06	0.24	In MSA	0.84	0.37
Married	0.59	0.49	Employed	0.63	0.48
# Dependents	0.83	1.22	Family Income/1K	50.63	38.45
High School Diploma	0.60	0.49	Health Fair	0.13	0.34
College Degree	0.29	0.46	Health Poor	0.05	0.22
Immigrant	0.07	0.26	Other Condition	0.64	0.48
Citizen	0.98	0.15	Functional Limitation	0.29	0.45
Northeast	0.26	0.44			

Notes:

1.Unlike the other two surveys, in this survey income is not top-coded at 50K.

2.Other condition is a binary variable equal to one if the individual has any of the following conditions (with prevalence in parentheses): asthma (0.080), diabetes (0.089), high blood pressure (0.234), arthritis (0.306), physical disability (0.064), COPD (0.062), cancer (0.023), neurological problem (0.023), stroke or other form of paralysis (0.019), heart problem (0.063), chronic back problem (0.208), stomach problems (0.087), liver condition (0.007), chronic headaches (0.133), urination problems (0.056), or chronic pain (0.112).

3.Functional Limitation is a binary variable equal to one if the individual is limited a lot in vigourous or moderated activities or in climbing stairs.

4.Unlike the NHIS and NCS-R, I coded "High School Diploma" as 1 iff the individual has a high school diploma but no college degree.

Table 6A: PUMS Explanatory Variable Moments					
Variable	Mean	Std Dev	Variable	Mean	Std Dev
Female	0.53	0.50	Family Income ($1K)	35.61	17.13
Age/100	0.36	0.22	Family Income > 50	0.46	0.50
Black	0.14	0.35	Northeast	0.00	0.00
Other Race	0.03	0.17	Midwest	0.00	0.00
Hispanic	0.02	0.15	South	1.00	0.00
Married	0.41	0.49	In MSA	1.00	0.00
Divorced	0.09	0.28	Work Disability Limits Work	0.08	0.28
Widowed	0.04	0.20	Work Disability Prevents Work	0.00	0.00
HS Diploma	0.67	0.47	Has Mobility Disability	0.05	0.22
College Degree	0.27	0.44			

Notes:

1.The base status for marital status is never married.

2.Family Income is censored at 50.

in PUMS. Thus, although, in theory, this variable could have been a useful Q variable, it is not because it has no variation.

The differences in moments between NHIS and PUMS, other than those caused directly by geography, are small or moderate. The PUMS sample is a little younger, more educated, and wealthier. The only significant differences are in racial composition where PUMS has a much smaller proportion of Hispanics and those of other races.

Those variables in NHIS that are not in PUMS include *veteran*, *health fair*, *health poor*, *height/weight*, *has medical condition*, *has ADL problem*, *has IADL problem*, and *has functional limitations*.[27] These are simulated using the methodology described in Section 3.2, resulting in simulated moments displayed

[27] Also, there is a small number of observations for which *income* is missing.

Table 6B: Simulated PUMS Explanatory Variable Moments					
Variable	Mean	Std Dev	Variable	Mean	Std Dev
Veteran	0.15	0.35	Has Medical Condition	0.13	0.34
Health Fair	0.09	0.29	Has ADL Problem	0.02	0.13
Health Poor	0.04	0.19	Has IADL Problem	0.07	0.25
Height/Weight	2.46	0.57	Has Functional Limitations	0.14	0.34

in Table 6B. All of the first moments in Table 6B are the same as those in Table 2C for corresponding NHIS variables.

4.5 Community Tracking Survey

The Community Tracking Survey (CTS) is a cross-section of 53138 observations on individuals (with clustering within families) from 60 communities[28] across the United States. It has a moderately-sized list of demographic, economic, health insurance, physical health, mental health, and health care utilization questions. Among other models, Stern et al. (2010) estimates a correlated probit model for depression,[29] allowing for a wide set of personal characteristics, community characteristics,[30] interactions between community and personal characteristics, and site dummy variables. The community dummy variables control for community effects not captured by the observed community characteristics included directly in the model. The included community characteristics mainly fall into four categories: demographic, economic, ruralness, and health care provision. Even after controlling for these community characteristics, the variation in community dummies is large. I discuss the implications of this in Section 5.4 below.

4.6 Variation in Prevalence Reporting Across Surveys

Table 7 presents estimates of mental health problem prevalence from four datasets.[31] The first three columns correspond to the datasets used in this research. The last comes from estimates reported in Robins and Regier (1991),[32] based on the Epidemiologic Catchment Area (ECA). One sees wide variation across surveys in the way mental health problems are classified. For example, *panic attacks* are reported separately in the NSADMHP and ECA but not in the NHIS or NCS-R, while *dysthymia* is reported separately in the NSADMHP and NCS-R

[28] A community is typically a collection of counties in close geographic proximity.

[29] The correlation is across individuals within the same family.

[30] Community characteristics come from merging with the Area Resources File and are county specific.

[31] Kessler et al (2005) reports prevalence rates for NCS-R different than in Table 7. They are different partially because of sample selection rules and partially because I aggregate diagnoses differently.

[32] Anxiety: Blazer et al. (1991), Table 8-3; Panic Attacks: Eaton, Dryman, and Weissman (1991), Table 7-2a; Depression: Weissman et al. (1991), Table 4-8; Schizophrenia: Keith, Regier, and Rae (1991), Table 3-2; Alcohol Abuse: Helzer, Burnam, and McEvoy (1991), Table 5.1; Drug Problem: Anthony and Helzer (1991), Table 6-4.

Table 7: Prevalence Rates Across Different Surveys				
		Frequency		
	NSADMHP	NHIS	NCS-R	ECA
Year	2001	1995	2002	1980-1985
Anxiety	4.50%	6.00%	19.10%	3.80%
Panic Attacks	6.90%			0.90%
Depression	11.80%	3.50%	6.80%	3.70%
Dysthymia	5.00%		1.50%	
Schizophrenia	1.00%	0.10%		1.00%
Psychosis	1.60%			
Alcohol Problem	5.70%		3.10%	6.80%
Drug Problem	1.90%		1.40%	2.00%
Substance Abuse Problem	7.60%	0.70%	4.50%	

Note: Estimates for the column labeled ECA are based on tables in Robins and Regier (1991).

but not in the NHIS.[33] Also, even when the same categorization is used, there is wide variation in reported prevalence. For example, in the NCS-R, 19.1% of respondents report having anxiety problems, while, for the other three surveys, anxiety prevalence ranges between 3.8% and 6.0%. There is also wide variation for depression and substance abuse problems.[34]

One might hypothesize that the variation occurs because the NHIS relies on self-reports while at least the NSADMHP and NCS-R rely on answers to screening questions frequently used in diagnosis. Such a hypothesis would require that people make large mistakes in self-diagnosis. However, this hypothesis does not work because the reported prevalence rates between NSADMHP and NCS-R also vary quite a lot. I have no explanation for the variation in diagnoses between NSADMHP and NCS-R.

One might conjecture that self-report in the NHIS occurs more often when the respondent's mental illness is more severe than the range imputed in the NCS-R and NSADMHP. In fact, Kessler et al. (1998) estimates a national prevalence rate for SMI of 6.2%, while the prevalence for any reported mental health problem in the NHIS is 10.0%. Narrow et al. (2002) proposes ways to reduce observed prevalence sympathetic to this idea. Mechanic (2003) argues that "the high estimates of mental illness have received much public attention and commentary, but they are not plausible representations of need. These high estimates lack credibility with many policymakers, and to the extent that they are believed, they may convey the impression that the treatment of mental illness is a bottomless pit, not a cost-effective way of investing new medical resources."

[33] *Dysthymia* is reported in the ECA but not by Robins and Regier (1991) in a way that is comparable to the other numbers in the table.

[34] The NHIS reports separate rates for drug and alcohol abuse, but I aggregate them for this analysis.

5 Results

5.1 Results using NHIS

I estimate three sets of models using NHIS data: a) one probit model for whether one has any mental health problem using the specification in equation (1); b) separate probit models for each of the nine different mental health diagnoses listed in Table 2A using the model specification in equation (2) but with no covariance structure; and c) a multivariate probit (MVP) model for the nine different mental health diagnoses using the model specification in equation (2) and with a general covariance structure. The model for *dementia* results in no significant estimates and otherwise strange results, probably because of small sample sizes for people with dementia.

5.1.1 Univariate Estimation Results

I begin by focusing on the one probit model for equation (1) and the eight separate probit models using equation (2). These results are reported in Table 8. The results imply that African-Americans, Hispanics, married people, wealthier people, and people in the Northeast and South report lower frequency of mental health problems. On the other hand, veterans and people with physical health problems report higher frequency of mental health problems. As a general rule, the effect of *age* on mental health problems, as displayed in Figure 3, increases with *age* until the late thirties or forties and then significantly declines.[35] The results for *gender* and *education* are mixed or statistically insignificant.[36] On the whole, these results are similar to those in the literature (see, for example, Robins and Regier, 1991; Kessler et al., 2005; Baldwin, 2005; Stern et al., 2010). Exceptions include Keith, Regier, and Rae (1991) who finds that *gender* has no significant effect on *schizophrenia* while I find a statistically significant negative marginal effect (-0.220) for women. This may occur because of a difference in timing, different sampling schemes, or the difference between marginal and average effects. It is also worth noting the high correlation between measures of physical health (*health fair*, *health poor*, *have other condition*, *have IADL problem*, and *have functional limitations*) with each of the mental health problems included in this study. As with many of the explanatory variables in this analysis, it is not clear which way causation runs.[37]

One must be careful in interpreting these results as causal. For example, it might be that *marriage* mitigates mental health problems, but it might also be that having mental health problems makes it more difficult to marry or to

[35] Anthony and Helzer (1991, Table 6-17) finds important interactions between *age* and *gender* for *substance abuse*. I do not include such an interaction in my analysis.

[36] Keith, Regier, and Rae (1991) finds similar insignificant results for the effect of education on schizophrenia. It argues that the correlation between *age* and *education* explains the lack of effect. However, I control for *age* and still get statistically insignificant results.

[37] For example, Wells et al. (1989), Katon and Sullivan (1990), and Watanabe et al. (2008) document high comorbidity rates between physical and mental health problems. Among others, Ford et al. (1998), Glassman and Shapiro (1998), Mussleman et al. (1998), and Frasure-Smith and Lesperance (2005) provide support for causation going in both directions.

Table 8: Independent Probit Estimates from NHIS						
	Anxiety		Schizophrenia		Paranoia	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Constant	-3.222 **	0.198	-3.997 **	1.056	-4.186 **	0.797
Female	0.236 **	0.023	-0.220 **	0.082	-0.024	0.072
Age/100	10.685 **	1.278	8.301	7.609	12.101 **	5.489
(Age/100)**2	-19.972 **	2.548	-8.907	17.222	-22.191 *	11.719
(Age/100)**3	10.517 **	1.593	-0.249	12.299	10.506	7.903
Black	-0.236 **	0.032	0.135	0.097	-0.028	0.097
Other Race	-0.076 *	0.040	-0.035	0.151	-0.009	0.131
Hispanic	-0.139 **	0.030	-0.069	0.113	-0.085	0.105
Married	-0.147 **	0.031	-0.716 **	0.097	-0.295 **	0.093
Divorced	0.148 **	0.037	-0.381 **	0.106	-0.086	0.106
Widowed	0.014	0.045	-0.509 **	0.190	-0.013	0.152
Veteran	0.085 **	0.033	0.072	0.112	0.229 **	0.095
HS Diploma	0.011	0.025	0.105	0.097	0.013	0.080
College Degree	0.020	0.028	-0.276 *	0.145	-0.036	0.110
Family Income	-0.012 **	0.001	-0.008 **	0.003	-0.011 **	0.003
Big Family Income	0.057 *	0.035	0.032	0.166	-0.065	0.153
Northeast	-0.129 **	0.031	-0.029	0.108	-0.173 *	0.099
Midwest	-0.038	0.029	-0.069	0.108	-0.199 **	0.091
South	-0.062 **	0.026	-0.277 **	0.104	-0.306 **	0.096
In MSA	0.063 **	0.025	-0.011	0.095	-0.092	0.081
Health Fair	0.492 **	0.027	0.446 **	0.101	0.512 **	0.088
Health Poor	0.735 **	0.037	0.625 **	0.116	0.744 **	0.103
Height/Weight	0.001	0.001	-0.002	0.002	0.012	0.060
Have Other Condition	0.472 **	0.025	0.298 **	0.085	0.446 **	0.076
Have ADL Problem	0.075	0.050	-0.153	0.180	0.036	0.139
Have IADL Problem	0.256 **	0.031	0.479 **	0.095	0.515 **	0.082
Have Functnal Limitns	0.435 **	0.027	-0.166 *	0.100	-0.214 **	0.090

Table 8 (Continued): Independent Probit Estimates from NHIS						
	Bipolar		Depression		Personality Disorder	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Constant	-3.715 **	0.538	-3.769 **	0.233	-3.168 **	0.298
Female	0.160 **	0.059	0.225 **	0.028	0.007	0.036
Age/100	7.790 **	3.876	13.897 **	1.528	9.982 **	1.986
(Age/100)**2	-14.760 *	8.685	-28.225 **	3.084	-21.877 **	4.146
(Age/100)**3	6.768	6.078	15.854 **	1.942	12.468 **	2.696
Black	-0.258 **	0.078	-0.263 **	0.038	-0.200 **	0.048
Other Race	-0.142	0.107	-0.047	0.048	0.043	0.059
Hispanic	-0.158 **	0.072	-0.200 **	0.036	-0.216 **	0.047
Married	-0.319 **	0.070	-0.147 **	0.036	-0.293 **	0.044
Divorced	0.086	0.075	0.176 **	0.042	0.058	0.052
Widowed	-0.290 **	0.145	-0.046	0.057	-0.012	0.076
Veteran	0.248 **	0.078	0.151 **	0.040	0.213 **	0.049
HS Diploma	0.191 **	0.066	-0.009	0.030	0.001	0.040
College Degree	-0.099	0.068	0.024	0.035	-0.064	0.049
Family Income	-0.007 **	0.002	-0.011 **	0.001	-0.009 **	0.002
Big Family Income	0.160 **	0.080	-0.015	0.043	-0.074	0.062
Northeast	-0.151 *	0.079	-0.141 **	0.038	-0.132 **	0.048
Midwest	0.029	0.067	-0.038	0.035	-0.211 **	0.048
South	-0.029	0.063	-0.079 **	0.032	-0.177 **	0.041
In MSA	0.067	0.061	0.060 **	0.030	0.118 **	0.041
Health Fair	0.470 **	0.063	0.526 **	0.032	0.470 **	0.042
Health Poor	0.541 **	0.082	0.788 **	0.041	0.641 **	0.054
Height/Weight	0.004 *	0.002	0.001	0.001	0.003 *	0.001
Have Other Condition	0.282 **	0.060	0.498 **	0.029	0.578 **	0.038
Have ADL Problem	0.147	0.115	0.127 **	0.054	0.173 **	0.070
Have IADL Problem	0.278 **	0.074	0.357 **	0.036	0.285 **	0.046
Have Functnal Limitns	0.060	0.064	0.299 **	0.033	0.107 **	0.044

Table 8 (Continued): Independent Probit Estimates from NHIS						
	Substance Abuse		Other Mental Health Problem		Overall	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Constant	-3.799 **	0.565	-2.897 **	0.216	-2.759 **	0.159
Female	-0.468 **	0.050	0.298 **	0.025	0.258 **	0.019
Age/100	15.353 **	4.179	6.595 **	1.436	9.794 **	1.043
(Age/100)**2	-30.671 **	9.658	-11.974 **	2.970	-18.766 **	2.109
(Age/100)**3	16.020 **	7.010	5.203 **	1.926	9.883 **	1.336
Black	-0.095	0.064	-0.209 **	0.036	-0.251 **	0.027
Other Race	-0.072	0.084	0.007	0.042	-0.036	0.033
Hispanic	-0.239 **	0.063	-0.152 **	0.033	-0.187 **	0.026
Married	-0.304 **	0.057	-0.077 **	0.033	-0.151 **	0.026
Divorced	0.029	0.068	0.122 **	0.040	0.152 **	0.031
Widowed	0.098	0.126	0.053	0.053	0.007	0.040
Veteran	0.272 **	0.064	0.134 **	0.036	0.103 **	0.027
HS Diploma	-0.138 **	0.051	0.017	0.029	-0.004	0.022
College Degree	-0.347 **	0.076	-0.099 **	0.030	-0.046 **	0.023
Family Income	-0.014 **	0.002	-0.006 **	0.001	-0.010 **	0.001
Big Family Income	0.188 **	0.080	-0.004	0.036	0.038	0.028
Northeast	-0.142 **	0.068	-0.057 *	0.033	-0.103 **	0.026
Midwest	-0.045	0.062	0.013	0.032	-0.006	0.024
South	-0.165 **	0.057	-0.057 *	0.029	-0.056 **	0.022
In MSA	0.092 *	0.054	0.081 **	0.028	0.079 **	0.021
Health Fair	0.373 **	0.059	0.244 **	0.032	0.422 **	0.024
Health Poor	0.457 **	0.078	0.249 **	0.044	0.613 **	0.035
Height/Weight	0.002	0.002	0.000	0.001	0.000	0.001
Have Other Condition	0.240 **	0.056	0.394 **	0.028	0.504 **	0.022
Have ADL Problem	-0.044	0.136	0.030	0.061	0.141 **	0.047
Have IADL Problem	-0.021	0.074	0.262 **	0.038	0.307 **	0.029
Have Functnal Limitns	0.220 **	0.065	0.378 **	0.030	0.466 **	0.024

Note: Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 10% level.

remain married. The same point applies to all of the estimates. Fortunately, for this research, this is not a problem in that the results in Table 8 are being used only to project local characteristics onto local prevalence rates. This exercise is robust to endogeneity problems. Once the joint density of the latent variables associated with the explanatory variables listed in Table 8 is estimated using the methodology described in Section 3.2, one can predict local mental health problem prevalence rates using the methodology described in Section 3.3. The results of this exercise are reported in Table 9 along with NHIS mean prevalence rates for comparison. The deviations between the mean NHIS results and the local results are mainly due to differences in the distribution of *age* (the local population is younger), the small size of the Hispanic population, and the fact that the local area is an MSA in the South.

Figure 4 shows the density of mental health problem probabilities in the local population for the most common mental health problems. While it is clear that most individuals have very small probabilities of having a mental health problem, there are a significant number who have probabilities well over 10%. I estimate that 28% have probabilities of having anxiety greater than 10%, 15% have probabilities of having depression greater than 10%, and 48% have probabilities of having some mental health problem greater than 10%. At the other end of the distribution, 12% have probabilities of having anxiety less than 1%, 27% have probabilities of having depression less than 1%, and 5% have probabilities of having some mental health problem less than 1%. One could identify the set of observable characteristics that lead to high rates of mental health problems and direct marketing or actual services at that group of people. One also can use the information provided in these results to plan for changes

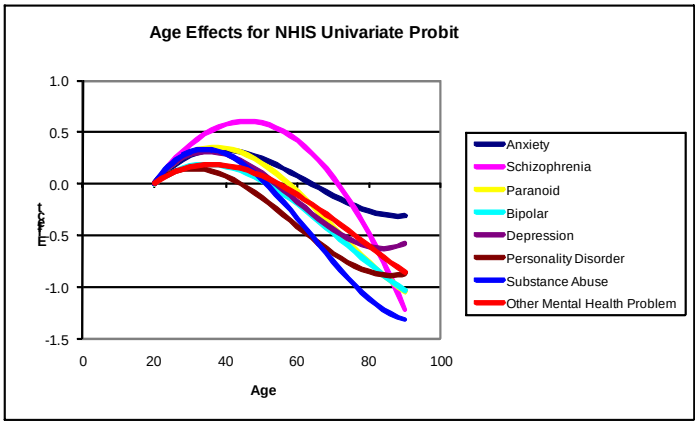

Figure 3: Age Effects for NHIS Univariate Probit

Table 9: Summary of Estimated Mental Health Prevalence			
	US NHIS	Local	
Variable	Mean	Mean	Std Dev
Anxiety	0.060	0.052	0.085
Schizophrenia	0.002	0.001	0.004
Paranoia	0.003	0.002	0.007
Bipolar	0.005	0.007	0.014
Depression	0.035	0.032	0.066
Personality Disorder	0.015	0.017	0.037
Substance Abuse	0.007	0.006	0.013
Other Mental Health Problem	0.039	0.034	0.046
Overall	0.098	0.087	0.115

in local mental health associated with local changes in demographics.

5.1.2 Multivariate Estimation Results

Next, I discuss results for the multivariate probit model. The literature finds that correlations among incidence of different mental health problems (i.e., co-morbidity) is very important (e.g., Kessler et al., 2005). In initial estimation attempts, I found that the high degree of collinearity among the constant, *age*, age^2, and age^3 led to poor estimation results. To solve this problem, one can construct orthonormal polynomials in *age* so that flexibility is maintained and yet the three *age* terms are, by construction, orthogonal.[38] The orthogonal

[38] The coefficients associated with each polynomial depend upon the sample density of age in the NCS-R, and they are listed in the notes to Table 9. See, for example, Chihara (1978) for a discussion of orthonormal polynomials.

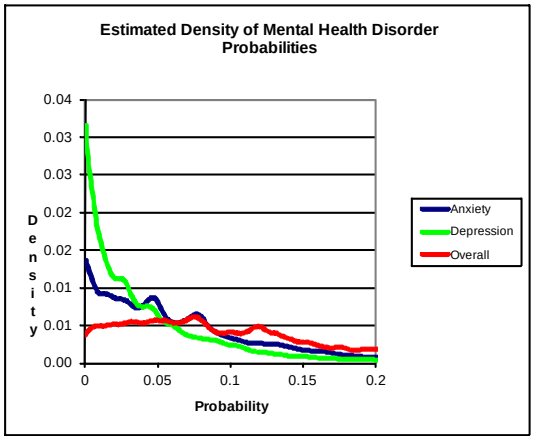

Figure 4: Estimated Density of Mental Health Disorder Probabilities

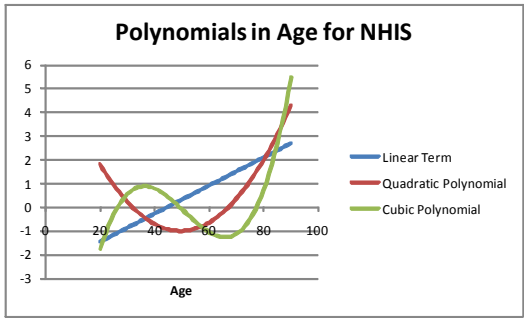

Figure 5: Polynomials in Age for NHIS

polynomials in *age* depend on the sample density of *age*, and those used in this exercise are presented in Figure 5.

The multivariate probit estimates are reported in Tables 10 and 11. The explanatory variable effects (α in equation (2)) are reported in Table 10. It is interesting to compare them to those for the univariate probit model estimates reported in Table 8. Figure 6 provides a scatter plot for all of the estimates except for the constant and the polynomial *age* effects. The estimates are almost perfectly proportional to each other with the multivariate probit estimates being 3/4 of the univariate probit estimates. However, as can be seen in Figure 7, the standard errors associated with the multivariate probit estimates are approximately 1.75 times as large as the standard errors associated with the univariate probit estimates.

The estimated *age* effects for the multivariate probit model, displayed in Figure 8, are pretty similar to those for the univariate probit models displayed

Table 10: Multivariate Probit Estimates from NHIS						
	Anxiety		Schizophrenia		Paranoia	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Constant	-1.155 **	0.081	-2.033 **	0.300	-2.283 **	0.398
Female	0.166 **	0.037	-0.167	0.119	-0.011	0.123
Linear Age Term	-0.083 **	0.020	-0.076	0.115	-0.172 **	0.085
Quadratic Polynomial in Age	-0.085 **	0.017	-0.206 *	0.127	-0.147 *	0.076
Cubic Polynomial in Age	0.042 **	0.015	-0.019	0.110	0.038	0.075
Black	-0.151 **	0.053	0.149	0.154	0.006	0.183
Other Race	-0.062	0.066	-0.059	0.202	-0.075	0.242
Hispanic	-0.093 *	0.049	-0.022	0.165	-0.029	0.185
Married	-0.102 **	0.052	-0.556 **	0.147	-0.223	0.151
Divorced	0.117 **	0.063	-0.247	0.168	-0.011	0.185
Widowed	0.021	0.073	-0.410	0.337	-0.017	0.324
Veteran	0.067	0.054	0.068	0.158	0.201	0.180
HS Diploma	0.008	0.040	0.070	0.154	-0.012	0.132
College Degree	0.015	0.044	-0.228	0.239	-0.008	0.190
Family Income	-0.009 **	0.002	-0.005	0.005	-0.008	0.006
Big Family Income	0.035	0.055	-0.028	0.257	-0.086	0.235
Northeast	-0.087 *	0.051	0.012	0.169	-0.121	0.173
Midwest	-0.023	0.047	-0.027	0.173	-0.118	0.153
South	-0.040	0.043	-0.187	0.157	-0.233 *	0.152
In MSA	0.048	0.040	-0.008	0.146	-0.061	0.143
Health Fair	0.359 **	0.047	0.377 **	0.149	0.426 **	0.149
Health Poor	0.538 **	0.077	0.490 **	0.188	0.629 **	0.205
Height/Weight	0.000	0.001	-0.003	0.004	0.009	0.088
Have Other Condition	0.333 **	0.043	0.232 *	0.127	0.349 **	0.132
Have ADL Problem	0.062	0.101	-0.014	0.297	0.070	0.262
Have IADL Problem	0.184 **	0.058	0.285 **	0.148	0.367 **	0.147
Have Functional Limitations	0.310 **	0.046	-0.154	0.145	-0.081	0.148

Table 10 (Continued): Multivariate Probit Estimates from NHIS						
	Bipolar		Depression		Personality Disorder	
Variable	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Constant	-2.435 **	0.229	-1.793 **	0.137	-1.192 **	0.161
Female	0.142 *	0.089	0.204 **	0.055	0.010	0.064
Linear Age Term	-0.193 **	0.057	-0.208 **	0.030	-0.241 **	0.034
Quadratic Polynomial in Age	-0.112 *	0.061	-0.108 **	0.025	-0.073 **	0.029
Cubic Polynomial in Age	0.027	0.054	0.076 **	0.023	0.051 *	0.027
Black	-0.181	0.132	-0.194 **	0.080	-0.138 *	0.089
Other Race	-0.161	0.180	-0.067	0.102	-0.008	0.106
Hispanic	-0.110	0.112	-0.171 **	0.072	-0.164 **	0.083
Married	-0.270 **	0.108	-0.131 *	0.074	-0.251 **	0.082
Divorced	0.116	0.121	0.186 **	0.090	0.084	0.102
Widowed	-0.202	0.221	-0.016	0.114	0.001	0.136
Veteran	0.225 *	0.127	0.152 *	0.079	0.206 **	0.084
HS Diploma	0.154	0.103	-0.010	0.062	0.003	0.070
College Degree	-0.066	0.106	0.013	0.065	-0.048	0.079
Family Income	-0.005 *	0.003	-0.009 **	0.002	-0.007 **	0.003
Big Family Income	0.088	0.123	-0.032	0.080	-0.097	0.102
Northeast	-0.083	0.123	-0.109	0.077	-0.095	0.087
Midwest	0.039	0.105	-0.024	0.070	-0.170 **	0.084
South	-0.003	0.100	-0.069	0.064	-0.149 **	0.071
In MSA	0.039	0.094	0.059	0.059	0.106	0.071
Health Fair	0.412 **	0.106	0.492 **	0.077	0.419 **	0.084
Health Poor	0.451 **	0.157	0.746 **	0.111	0.571 **	0.108
Height/Weight	0.003	0.005	0.000	0.002	0.002	0.002
Have Other Condition	0.227 **	0.099	0.445 **	0.068	0.490 **	0.075
Have ADL Problem	0.162	0.220	0.130	0.147	0.182	0.139
Have IADL Problem	0.193 *	0.119	0.326 **	0.085	0.236 **	0.092
Have Functional Limitations	0.103	0.105	0.281 **	0.069	0.131 *	0.082

Table 10 (Continued): Multivariate Probit Estimates from NHIS						
	Substance Abuse			Other Mental Health Problems		
Variable	Estimate		Std Err	Estimate		Std Err
Constant	-1.534	**	0.156	-1.624	**	0.095
Female	-0.384	**	0.070	0.241	**	0.039
Linear Age Term	-0.275	**	0.064	-0.154	**	0.022
Quadratic Polynomial in Age	-0.143	**	0.060	-0.100	**	0.019
Cubic Polynomial in Age	0.060		0.052	0.024		0.018
Black	-0.053		0.085	-0.147	**	0.056
Other Race	-0.081		0.108	-0.013		0.067
Hispanic	-0.174	**	0.087	-0.122	**	0.053
Married	-0.236	**	0.077	-0.058		0.052
Divorced	0.050		0.095	0.116	*	0.065
Widowed	0.053		0.178	0.065		0.086
Veteran	0.204	**	0.088	0.120	**	0.054
HS Diploma	-0.104		0.069	0.014		0.047
College Degree	-0.261	**	0.094	-0.083	*	0.044
Family Income	-0.010	**	0.003	-0.004	**	0.002
Big Family Income	0.097		0.105	-0.006		0.053
Northeast	-0.103		0.094	-0.038		0.052
Midwest	-0.020		0.082	0.013		0.050
South	-0.109		0.075	-0.044		0.046
In MSA	0.065		0.075	0.064		0.043
Health Fair	0.308	**	0.082	0.217	**	0.056
Health Poor	0.390	**	0.114	0.217	**	0.086
Height/Weight	0.001		0.003	0.000		0.001
Have Other Condition	0.179	**	0.078	0.319	**	0.049
Have ADL Problem	0.023		0.196	0.039		0.117
Have IADL Problem	-0.035		0.107	0.223	**	0.069
Have Functional Limitations	0.184	**	0.088	0.302	**	0.050

Notes:

1.Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 10% level.

2.Orthonormal polynomial age coefficients are: a) constant [1.000]; b) linear [-2.640,5.900]; c) quadratic [6.875,-31.807,32.136]; and d) cubic [-16.855,119.976,-256.893,167.981]

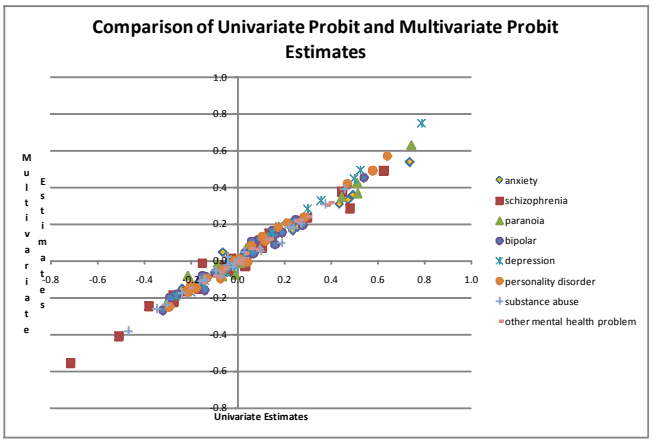

Figure 6: Comparison of Univariate Probit and Multivariate Probit Estimates

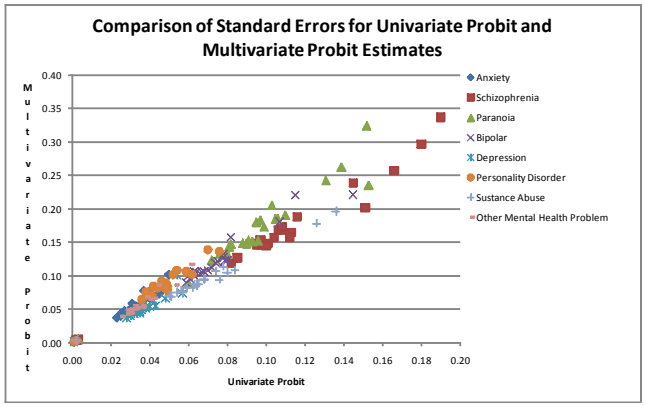

Figure 7: Comparison of Standard Errors for Univariate Probit and Multivariate Probit Estimates

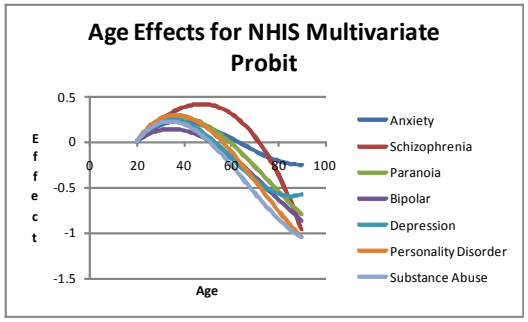

Figure 8: Age Effects for NHIS Multivariate Probit

in Figure 3.[39] In particular, both exhibit increasing prevalence for young adults and then declining prevalence starting in the late thirties (and a little later for *schizophrenia*).

The estimated covariance matrix of the multivariate normal errors defined in equation (3) is presented in Table 11. The diagonal elements of Ω are all restricted to be one for identification purposes. All of the other covariance terms are large and statistically significant. This is strong evidence of the comorbidity phenomenon discussed in the literature (e.g., Kessler et al., 2005).Figure 9 displays the densities of prevalence probabilities for anxiety, depression, and the existence of any mental health problem based on the multivariate probit estimates from Tables 10 and 11. One can see by comparing Figure 9 to Figure 4 (for the univariate probit estimates) some significant differences in estimated mental health problem densities. The most notable difference is that the den-

[39] Also, since the sample density of *age* is not very different, the coefficients associated with the orthonormal polynomials are pretty similar (see notes in Tables 10 and 12).

Table 11: Estimates of the Covariance Matrix for the Multivariate Probit Model

	1	2	3	4	5	6	7	8
1	1.000 +							
2	0.652 **	1.000 +						
3	0.772 **	0.560 **	1.000 +					
4	0.750 **	0.588 **	0.601 **	1.000 +				
5	0.773 **	0.551 **	0.621 **	0.586 **	1.000 +			
6	0.766 **	0.588 **	0.600 **	0.602 **	0.623 **	1.000 +		
7	0.548 **	0.416 **	0.420 **	0.421 **	0.337 **	0.417 **	1.000 +	
8	0.548 **	0.425 **	0.397 **	0.427 **	0.458 **	0.479 **	0.281 **	1.000 +

Notes:

1.Items with double stars are statistically significant at the 5% level, and items with pluses are restricted to equal one.
2.Order of Conditions: 1) Anxiety, 2) Schizophrenia, 3) Paranoia, 4) Bipolar, 5) Depression, 6) Personality Disorder, 7) Substance Abuse, and 8) Other Mental Health Problem.

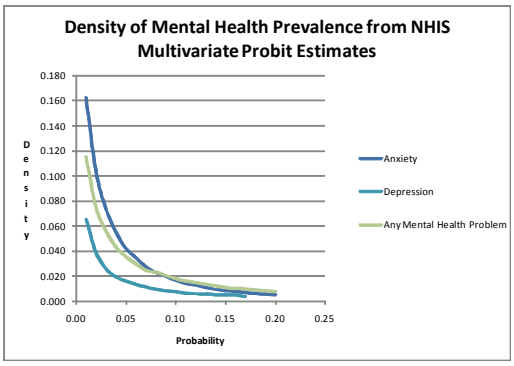

Figure 9: Density of Mental Health Prevalence from NHIS Multivariate Probit Estimates

sity for any mental health problem in Figure 9 continuously increases as the probability goes to zero, while the density for overall mental health in Figure 4 flattens out for probabilities below 0.075. The density curve in Figure 4 is based on estimates from a probit equation where the dependent variable is *existence of any mental health problem* (see equation (1)), while the density curve in Figure 9 is based on estimates from the multivariate probit equations (see equations (2) and (3)). The multivariate probit equation imposes the structure that

$$\Pr\left[\overrightarrow{y}_i = 0 \mid X_i\right] = \int_{u<-X_i\alpha} dF\left(u \mid \Omega\right)$$

where $\overrightarrow{y}_i = (y_{i1}, y_{i2}, .., y_{iJ})'$ which is substantively more structure than imposed by the probit model. The fact that the estimated densities are quite different suggests that the joint normality assumption in equation (3) is not consistent with the data. One might think about estimating the joint density semi- or nonparametrically. One possibility is to use copulas (e.g., see Nelson, 1999).

Table 12: NCS-R Probit Estimates					
Variable	Estimate	Std Err	Variable	Estimate	Std Err
Constant	-1.422 **	0.083	Employed	0.097 **	0.041
Female	0.256 **	0.033	Rcve Public Assist	0.332 **	0.095
Linear Age Term	-0.376 **	0.022	Health Fair	0.092	0.087
Qudratic Polynml in Age	-0.025	0.018	Health Poor	0.456 **	0.196
Cubic Polynomial in Age	0.036 **	0.017	Northeast	0.019	0.050
Black	-0.022	0.050	Midwest	-0.023	0.046
Other Race	0.013	0.075	South	-0.011	0.044
Hispanic	0.011	0.057	Medical Condition	0.411 **	0.036
Married	-0.325 **	0.048	ADL Problem	-0.069	0.150
Divorced/Widowed	0.101 *	0.057	Functional Limitation	0.401	0.355
High School Diploma	-0.222 **	0.050	Citizen	0.600 **	0.039
College Degree	-0.191 **	0.038	Immigrant	0.101 *	0.061
			Attends Religious		
Family Income ($1K)	0.016 **	0.002	Services Frequently	-0.122 *	0.069
Family Income > 50K	-0.234 **	0.054	Religion Important	0.046	0.035

Notes:

1.Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 10% level.

2.Orthonormal polynomial age coefficients are: a) constant [1.000]; b) linear [-2.618,5.789]; c) quadratic [6.528,-30.339,30.692]; and d) cubic [-16.283,116.787,-250.224,163.195]

5.2 Results Using NCS-R

I estimated a probit model using the NCS-R data for whether one has any mental health problem using the specification in equation (1). Based on the results in Tables 8 and 10, it seems to be important to allow for *age* to affect prevalence flexibly. However, in the NCS-R data, the constant, *age*, age^2, and age^3 are almost perfectly colinear. So, again I use orthonormal polynomials. The estimation results for this model are reported in Table 12.

The results imply that married people and people with high school or college educations report lower frequency of mental health problems. On the other hand, women, employed people, people receiving public assistance, citizens, and people in poor health or who have medical conditions report higher frequency of mental health problems. The effect of *income* is mixed: prevalence rises for incomes less than $50K but is lower for people with incomes above $50K. As a general rule, the effect of *age* on mental health problems, as represented by the solid curve in Figure 10, decreases with *age*. The results for *race* and *ethnicity* are statistically insignificant. There are some significant differences between these estimates and those for the NHIS in Tables 8 and 10. In particular, for NCS-R, racial and ethnicity variables have no effect after controlling for other variables, and income effects are reversed. It is not clear why such different results occur. Using data from the ECA, Kessler et al. (1996) finds results consistent with those reported in Table 12 for *female*, *marital status*, and *education*; inconsistent results for *income*; and statistically insignificant effects for *age*, *race*, and *region*.[40]

[40] Kessler et al. (1996) does not control for the other variables included in Table 11.

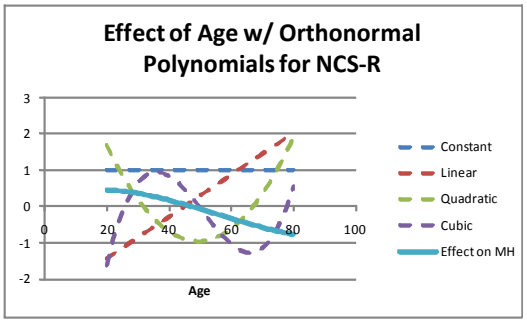

Figure 10: Effect of Age w/ Orthonormal Polynomials for NCS-R

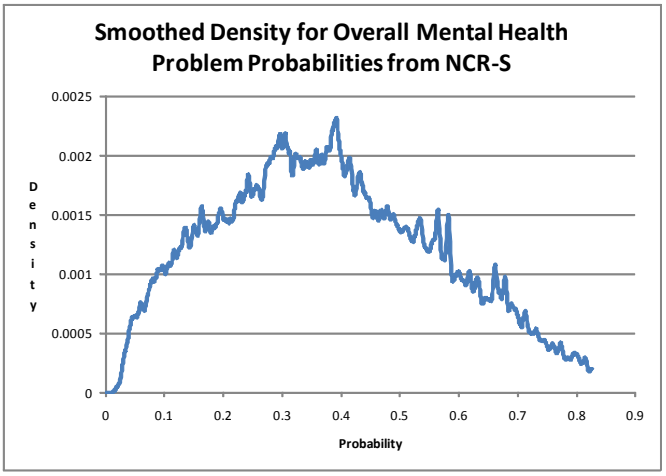

Figure 11: Smoothed Density for Overall Mental Health Problem Probilities from NCR-S

Once the joint density of the latent variables associated with the explanatory variables listed in Table 12 is estimated using the methodology described in Section 3.2, one can predict local mental health problem prevalence rates using the methodology described in Section 3.3. The results of this exercise result in an estimated overall prevalence rate of 38.5% as compared to the NHIS mean overall prevalence rate of 12.5% (see Table 9). The smoothed estimated density of the probability of having a mental health problem is displayed in Figure 11 (see Figure 4 for NHIS comparison). The surprising difference in magnitude between estimates coming from NHIS and from NCS-R are mostly due to the large magnitude in reported mental health problem prevalences in the two data sets. This is not a problem with the underlying econometric methodology; instead it is caused by variation in how mental health is measured across the two datasets.

Table 13: NSADMHP Probit Estimates					
Variable	Estimate	Std Err	Variable	Estimate	Std Err
Constant	-0.655 **	0.189	Citizen	0.024	0.159
Female	-0.085 **	0.041	Northeast	-0.061	0.069
Linear Age Term	-0.500 **	0.026	Southeast	-0.055	0.072
Quadratic Polynomial in Age	-0.178 **	0.024	Midwest	0.095	0.070
Cubic Polynomial in Age	0.048 *	0.025	Southwest	0.026	0.097
Black	-0.164 **	0.062	In MSA	0.068	0.077
Other Race	-0.348 **	0.130	Employed	-0.253	2.206
Hispanic	-0.004	0.086	Family Income/1K	0.000	0.057
Married	-0.319 **	0.045	Health Fair	0.361 **	0.050
# Dependents	-0.064 **	0.019	Health Poor	0.717 **	0.001
High School Diploma	-0.087	0.064	Other Condition	0.351 **	0.057
College Degree	-0.226 **	0.075	Functional Limitation	0.254 **	0.089
Immigrant	-0.159	0.107			

Notes:
1.Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 10% level.
2.Orthonormal polynomial age coefficients are: a) constant [1.000]; b) linear [-3.066,6.237]; c) quadratic [8.475,-36.166,34.799]; and d) cubic [-22.421,148.951,-303.028,191.068]

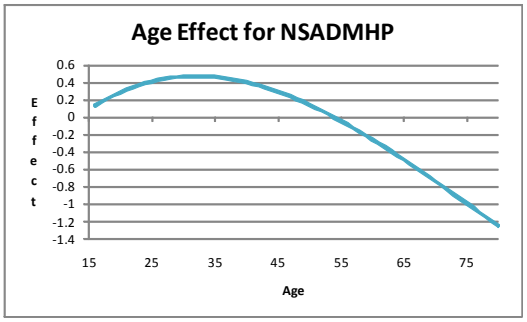

Figure 12: Age Effect for NSADMHP

5.3 Results Using NSADMHP

I estimate a probit model using the NCS-R data for whether one has any mental health problem using the specification in equation (1). The estimates are reported in Table 13. Women, blacks, married people, and people with increasing levels of education are less likely to have a mental health problem, while people in fair/poor health or with other medical conditions or functional limitations are more likely to have a mental health problem. The effect of *female* (-0.085) is opposite that in the NHIS (Table 8) or NCS-R (Table 12) and probably is highly biased by the oversampling rules associated with NSADMHP. Other estimates are qualitatively similar.

Figure 13 compares selected estimates from Table 13 for the NSADMHP to estimates from Table 11 for the NCS-R. Each ellipse[41] is a 95% confidence region for a particular estimate.[42] For example, the confidence interval for

[41] The confidence region for *health poor* looks like a line segment because the NSADMHP estimate is estimated very precisely.

[42] Confidence regions are ellipses because the two data sets provide independent estimates

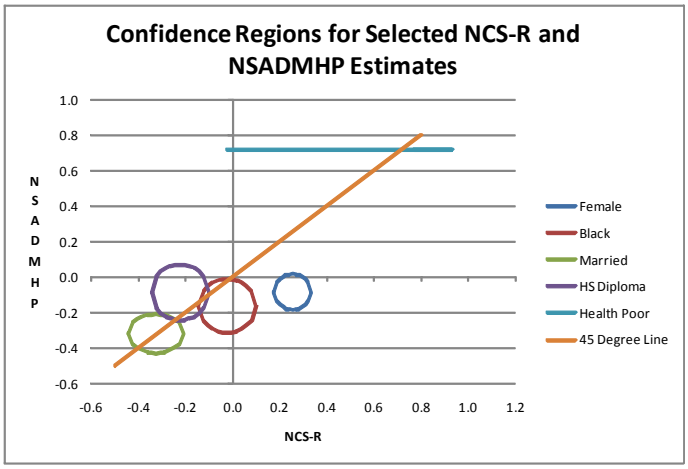

Figure 13: Confidence Regions for Selected NCS-R and NSADMHP Estimates

black is $[-0.120, 0.076]$ in the NCS-R and $[-0.286, -0.042]$ in the NSADMHP. For each estimate j, if the corresponding ellipse intersects the 45° line, then one can accept $H_0 : \beta_j^{NCS-R} = \beta_j^{NSADMHP}$. Thus, for those estimates represented in the figure, with the exception of *female*, no other null hypotheses are rejected.[43] Given the close proximity of the estimates, I do not report separate local prevalence estimates for the NSADMHP.

As was discussed in Section 4.3, the NSADMHP has two continuous measures of mental health: *MCS-12* and *MHI-5*. Ordinary least squares estimates of explanatory variable effects are reported in Table 14. For *MCS-12*, only *age*, *employment status*, *family income*, *health*, existence of other medical conditions,and some regional dummies have statistically significant effects. For *MHI-5*, *gender*, *age*, *race*, *marital status*, *education*, *employment status*, *family income*, health, and existence of other medical conditions and functional limitations all have statistically significant effects and in the direction one might expect. Also, almost twice as much of the variation in the data is explained for *MHI-5* relative to *MCS-12*. The correlation between residuals in the two equations is 0.58, suggesting that there is some important common unobserved determinant for both measures.The obvious question implied by the results in Table 14 is whether they can be used to estimate local prevalence of mental health problems. Represent the estimated equation associated with the *MHI-5* column of Table 14 as

$$m_i = X_i\widehat{\gamma} + \xi_i$$

where ξ_i is the error with estimated standard deviation $\widehat{\sigma}_\xi = 16.07$, and represent the estimated $\Pr[\text{Mental Health Problem} \mid m_i]$ reported in Figure 2 as

with different standard errors.

[43] Among the other parameters common to both models, the only other rejections are for *fair health* and *immigrant*.

Table 14: OLS Estimates for MCS-12 and MHI-5

	MCS-12		MHI-5	
Variable	Estimate	Std Err	Estimate	Std Err
Constant	46.308 **	0.694	81.042 **	2.018
Female	-0.153	0.155	-1.140 **	0.450
Age	0.857 **	0.094	3.969 **	0.274
Age**2	0.368 **	0.080	2.124 **	0.233
Age**3	-0.330 **	0.078	-1.133 **	0.227
Black	0.945 **	0.239	2.474 **	0.694
Other Race	-0.250	0.444	0.558	1.292
Hispanic	0.209	0.347	0.097	1.010
Married	0.159	0.174	2.947 **	0.505
# Depend	-0.054	0.072	-0.014	0.210
High School Diploma	0.135	0.256	3.278 **	0.745
College Degree	-0.125	0.293	2.982 **	0.853
Immigrant	0.099	0.374	-1.440	1.088
Citizen	-0.023	0.592	-1.503	1.721
Northeast	-0.395 *	0.204	-0.303	0.594
Southeast	-0.185	0.222	-0.258	0.645
Midwest	-0.565 **	0.216	-1.022 *	0.627
Southwest	-0.796 **	0.327	-2.832 **	0.952
In MSA	-0.279	0.207	-1.705 **	0.601
Employed	0.709 **	0.196	3.098 **	0.569
Family Income/1K	0.007 **	0.002	0.026 **	0.007
Health Fair	-3.446 **	0.239	-9.508 **	0.696
Health Poor	-7.487 **	0.375	-22.006 **	1.091
Other Condition	-1.432 **	0.171	-5.710 **	0.499
Functional Limitation	0.147	0.192	-3.746 **	0.558
R-Squared	0.144		0.226	

Notes:
1. Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 10% level.
2. The estimated correlation between the two equations is 0.580.

$\widehat{P}(m_i)$. Then, one can simulate $\xi_i^r \sim N(0, \widehat{\sigma}_\xi)$ along with any missing values of X_i as described in Section 3.2, construct $m_i^r = X_i\widehat{\gamma} + \xi_i^r$, and then simulate

$$p_i^r \sim Bernoulli\left(\widehat{P}(m_i^r)\right). \tag{4}$$

Performing the same procedure for $r = 1, 2, .., R$ independent times allows one to simulate the distribution of the probability of having mental health problems. However, there are a few problems with such an approach: a) Measures of *MHI-5* are less likely to exist in relevant national datasets;[44] b) $\Pr[\text{Mental Health Problem} \mid m_i]$ is a less precise measure of whether i has a mental health problem than is a direct measure; and c) the advantages of linearity disappear because p_i^r is nonlinear in m_i^r in equation (4).

Point (b) is a specific example of an important general point. The reason that this method provides a distribution of the probability of having a mental health problem rather than a distribution of having a mental health problem is because there is randomness associated with the prediction for any specific individual in the population. In other words, in the local population, one observes the variables that aid in predicting the existence of a mental health problem rather than observing a direct measure of mental health. The randomness is caused by a mixture of lack of clinical knowledge on how to predict mental health problems and limited data in any particular data set. To the degree that one has access to better data, one can reduce the variance of the predicted probability of having a mental health problem. In the limit, if psychologists and

[44] In fact, since *MHI-5* is a function of underlying answers about the existence of mental health problems, it is very unlikely that an *MHI-5* score would be reported without the inputs to the *MHI-5* score also being reported.

psychiatrists knew how to measure mental health without error and data were available locally on all of the inputs associated with measuring mental health, then the distribution of the probability of having mental health problems conditional on those inputs would become a degenerate distribution with all of its mass at either 0 or 1.

5.4 Community Fixed Effects and Random Effects

The analysis so far is subject to the criticism that there might be important community effects that are not being controlled for. To learn something about the magnitude of this problem, I use results from a correlated probit estimation for depression from Stern et al. (2010). The model uses data from the Community Tracking Survey (CTS), discussed in Section 4.5, to estimate a model with personal characteristics, community characteristics, interactions and 60 community fixed effects.[45] Note that the community fixed effects are capturing community effects not captured by the included observable community characteristics described in Section 4.5. It is worth noting that Stern et al. (2010) uses a more exhaustive set of community characteristics than used in Kessler et al. (1998), implying that community fixed effects would be present in its estimates as well.

I took someone with average personal and community characteristics $\overline{x}$ and then, using the estimated fixed effects $\left\{\widehat{\lambda_j}\right\}_{j=1}^{60}$ and the estimated other coefficients $\widehat{\delta}$, computed the distribution of

$$p_j = \Phi\left(\widehat{\lambda_j} + \overline{x}\widehat{\delta}\right)$$

over the 60 communities in the CTS. The results are displayed in Figure 14. The median probability of having depression is 0.085, and an 80% confidence interval around the median is $(0.051, 0.123)$. This strongly suggests that there are important community characteristics, some of which are difficult to identify, that affect mental health prevalence. It is not clear what can be done to mitigate this problem. Messer et al. (2004) assumes somewhat arbitrarily that the variation due to such fixed effects are 5%; i.e. they add 5% to each end of the confidence intervals. In fact, Figure 14 suggests that the 5% rule is quite reasonable. Leroux, Lei, and Breslow (1999) suggests ways to allow for spatial correlation in prevalence rates, and Stern et al. (2010) suggests ways to measure spatial correlation after controlling for community fixed effects of the sort implied by the structure of the CTS.

[45] Prasad and Rao (1999) and Opsomer et al. (2008) treat the community effects as random effects. Stern et al. (2010) treats them as fixed effects because a) it has a large number of observations per community and b) it does not have to assume the community effects are independent of observed community characteristics by treating them as fixed effects. Congdon (2009) looks at the effect of community characteristics on the prevalence of heart disease and finds that community characteristics are important in explaining some of the geographical variation in prevalence. However, Stern et al. (2010) finds important community-specific fixed effects even after controlling for a larger set of community characteristics than were found in Congdon (2009).

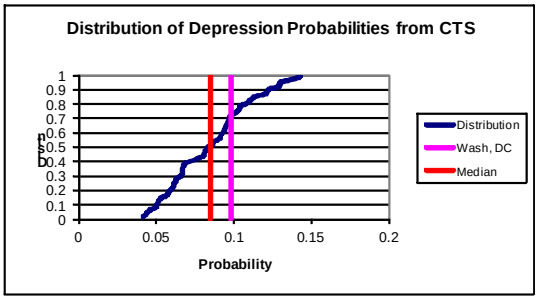

Figure 14: Distribution of Site Effects

Another possible solution is to use the estimated fixed effect for the CTS community closest to the local area. However, it is not obvious what the correct metric for proximity is. Using geographical proximity, Washington, DC is the closest community in the CTS to Charlottesville. Assuming Charlottesville has the same site effect as Washington DC results in adding 0.013 to the prevalence of depression. However, along most other relevant dimensions, Washington, DC is very different than Charlottesville, and it would be inappropriate to think of the two communities as having the same community characteristics. Other sites that one might think of as similar to Charlottesville in some metric involving population size (and its implied change in depression prevalence) include Huntington WV (+0.008), Wilmington NC (−.001), and Dothan AL (+0.052). On the other hand, using the same analysis from Stern et al. (2010) for *MCS-12*, the standard deviation of fixed effects for the same 60 sites is 0.64 which is quite small relative to the standard deviation of *MCS-12* in the NSADMHP reported in Table 5A. Thus, the significance of missing geography-specific fixed effects varies over different measures of mental health.

Another possible solution is to use the sampling information in the dataset (e.g., Little, 1991; Banerjee, Wall, and Carlin, 2003; Malec and Müller, 2008). Each observation is assigned to a different PSU/Strata. While the data do not identify the location of each PSU/Strata, two observations are from the same geographical area iff they have the same PSU/Strata number.[46] Thus, one can use the PSU/Strata number to construct a random effects dummy variable for each observation and the estimate the distribution of the PSU/Strata-specific random effect.[47]

As an example, I estimate the multivariate probit model (Table 10) including a single common PSU/Strata random effect with a normal distribution.[48] The estimate of the standard deviation was 0.095 with a standard error of 0.044.

[46] The NCR and NSADMHP have similar types of information.

[47] In theory, alternatively one could treat the effects as fixed. However, given the nonlinearity of the model, the fixed effects can not be differenced out except in very special cases (Chamberlain, 1980)..

[48] One could allow for a more flexible error structure at the expense of more CPU time and more demand on the data.

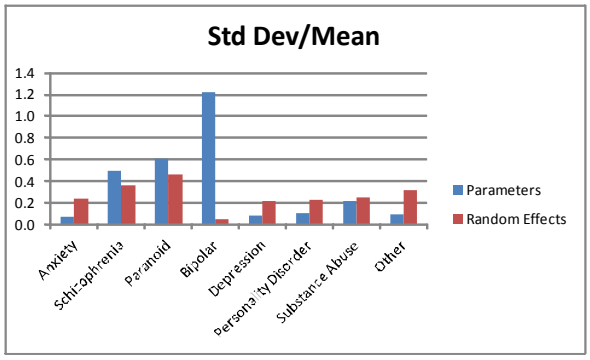

Figure 15: Standard Deviation/Mean

The estimates of the parameters associated with explanatory variables change very little or only proportionately to each other. For each diagnosis, I estimate an OLS model of the multivariate estimates including a random effect on the multivariate estimates excluding a random effect. The range of estimated OLS slopes is 0.773 to 1.003, and the range of R^2s is 0.952 to 0.997. The estimated standard deviation is relatively small and has very little effect on the other estimates. However, starting from a 0.085 median probability of depression, a 95% confidence interval for the median implied by the estimate of the random effect standard deviation is $[0.059, 0.119]$, providing results somewhat similar to the CTS results discussed above.

One also can decompose randomness of estimates into that caused by randomness in parameter estimates and that caused by the existence of the random effects discussed above. Figure 15 shows how much randomness in estimated mean prevalence rates is caused by each contributor. First of all, it is clear that, except for *bipolar* and *paranoid*, the mean prevalence rate is estimated quite precisely. The effect of random effects on randomness is relatively stable across different diagnoses, while estimation errors' effects vary significantly.

One of the goals of this paper is to estimate the density of mental health problems within a community. Figure 16 shows confidence intervals for the quantile estimates for *anxiety* and *depression* implied by a) randomness in parameter estimates and b) existence of random effects. For both diagnoses, the randomness due to the existence of random effects is larger than that due to randomness in parameter estimates.[49] The confidence intervals for *schizophrenia* and *paranoid* are much lower and tight because of the low prevalence of both. The same is true for *bipolar* and *personality disorder* though to a lesser degree. *Substance abuse* has similar results to *bipolar* and *personality disorder* for the first two quantile estimates, but it increases significantly both in level and width

[49] While the figure might lead one to believe that one cannot reject $H_0 : Q_1 = Q_2 = Q_3$ (where Q_j is the jth quantile), such a conclusion would be incorrect because it ignores the positive correlation among the three quantile estimates. In fact, almost all of the movement across realizations of the quantile estimates are just vertical shifts of all three together.

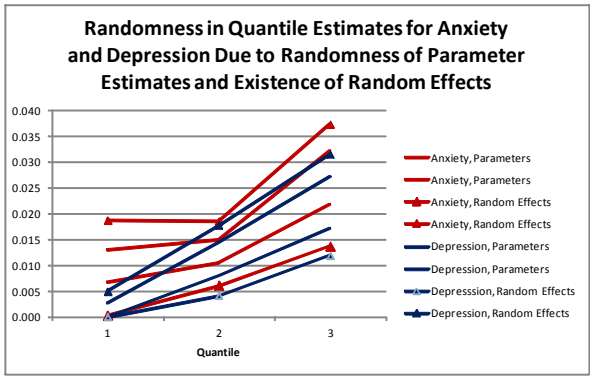

Figure 16: Randomness in Quantile Estimates for Anxiety and Depression Due to Randomness in Parameter Estimates and Existence of Random Effects

for the third quantile. *Other* has confidence intervals similar to *anxiety* and *depression*.[50] Overall, the results imply that it is important to control random effects.

5.5 Local Estimates

Tables 15 and 16 use the density estimates presented in Figures 4 and similar (unreported) density curves for the other diagnoses to predict the number of adults in the Charlottesville MSA with mental health problems. Using the NHIS estimates (Table 15), I can decompose the prediction across different diagnoses; for the NCS-R predictions (Table 16), I report only the overall prediction. One can see that the predictions differ by an order of magnitude. This occurs because the estimate of someone having a mental health problem in the Charlottesville MSA from the NHIS data is 0.087, and, from the NCS-R data, it is 0.384. These estimates are different because 10% of the observations in the NHIS report having a mental health problem while 29% of those in the NCS-R report having a mental health problem. In effect, the variation is not due to the methodology; rather it is caused by order-of-magnitude variation in the underlying survey data.

6 Policy Implications

One of the uses of prevalence estimation is to analyze the demand for local mental health services. In Virginia, publicly provided mental health services are provided by 40 community service boards (CSBs). In general, the CSBs provide mental health services, drug abuse services, and services for people

[50] Figures for diagnoses other than *anxiety* and *depression* are available from the author.

Table 15: Estimated Number of People with Various Mental Health Problems Using NHIS Estimates					
	Probability	Albemarle County	Charlottes-ville	Outlying Counties	Total
2006 Adult Population		72247	32446	68949	173642
Anxiety	0.052	3721	1671	3551	8943
Schizophrenia	0.001	94	42	90	226
Paranoia	0.002	137	62	131	330
Bipolar	0.007	491	221	469	1181
Depression	0.032	2276	1022	2172	5470
Personality Disorder	0.017	1207	542	1151	2900
Substance Abuse	0.006	441	198	421	1059
Other Mental Health Problem	0.034	2435	1093	2324	5852
Overall	0.086	6213	2790	5930	14933

Table 16: Estimated Number of People with Any Mental Health Problem Using NCS-R Estimates					
	Probability	Albemarle County	Charlottes-ville	Outlying Counties	Total
2006 Adult Population		72247	32446	68949	173642
Overall	0.384	27721	12449	26455	66625

with intellectual disabilities.[51] The CSB in the Charlottesville MSA is called the Region Ten Community Services Board.[52] For the most part, Region Ten provides services for people who are eligible for Medicaid or with low income. Using the PUMS data and my parameter estimates from Tables 8 and 12, I estimated the expected number of adults with mental health problems who possibly would receive services from Region Ten; i.e., are of interest for this particular policy analysis. In particular, I included only those people in the PUMS data who have income below $25K and who do not have a college degree. This approach is very different from the approach for estimating need in Ellis et al. (2009). On the one hand, the approach in Ellis et al. (2009) is much more ambitious because it strives to construct a credible estimate of the need for mental health services in a community for all community members, while my approach focuses only on potential recipients of public mental health services and makes no attempt to estimate individual demand. On the other hand, the approach in Ellis et al. (2009) does not attempt to measure the lack of demand caused by financing issues, while my analysis focuses on people with mental health problems who can receive services only through public providers. In fact, for example, in the Region Ten catchment area, the supply of mental health providers is quite large. But, for people without the financial resources

[51] See Virginia Department of Behavioral Health and Developmental Services (2010) or Brown, Guo, and Stern (2013) for more information about CSBs.

[52] In the interest of fair advertising, I should point out that I was on the board of directors of the Region Ten CSB when I wrote this paper.

Table 17: Estimated Number of People of Interest with Any Mental Health Problem

	Mean Predicted Probability	Adult Population	Proportion of Population	Adult Population of Interest	Predicted Population with Mental Illness
NHIS	0.083	173642	0.730	126759	10521
NCS-R	0.411	173642	0.668	115993	47696

Note: A person of interest has family income below $25K and no college education

to pay for such care, there is a real shortage of available services. Both types of analyses are useful, and both could be improved taking into account the advantages of the other.

The results of this exercise are reported in Table 15. Approximately 2/3 of the local population satisfies the exclusion criteria. Note that the prevalence of mental health problems is moderately higher than is reported in Tables 15 (for NHIS) and a bit lower than in Table 16 (for NCS-R). This occurs because of estimates associated with high income and college education.The estimated demand for public mental health services is reported in the last column of Table 17. As was the case when the whole population was used, the estimate depends critically on which national data is used to estimate the model. Between FY2008 and FY2010, the average number of unduplicated clients provided service at Region Ten was 4813. Using the conservative NHIS estimate of the number of people needing mental health care services, only 4813/10521 = 46% of those needing help received services. Using the NCS-R estimate, only 4813/47696 = 10% of those needing help received services. While the estimated number of people needing public mental health services varies greatly with the survey used (NHIS vs. NCS-R or NSADMHP), it is clear that there is a large shortage of services for those in need. Using the NCS-R, Wang, Demler, and Kessler (2002) reports that only 40% of those with SMI received mental health services in the previous 12 months; this is somewhat similar to our NHIS-based estimate, again suggesting a relationship between NHIS estimates and NCS-R and NSADMHP estimates. However, Wang et al. (2005) finds that 41.1% of those in the NCS-R with a mental health problem received some service. Aoun, Pennebaker, and Wood (2004) suggests that the gap between prevalence and mental health care use can be explained by "the discordance between diagnosis and disability, the determinants of and barriers to help-seeking behavior, the belief systems concerning appropriate treatments, and choice of health professionals;" i.e., people are choosing not to seek help. While this might be true for many of the 47696 predicted to need help based on the NCS-R, it is more likely the case that, for this group of people, especially the 10521 predicted to need care based on NHIS, that the significant barrier to service is cost (for private and public care) and

supply-side rationing (for public care). These estimates are consistent with Wang, Demler, and Kessler (2002), Kessler et al. (2005), and with studies cited in Hauenstein et al. (2006).

7 Conclusion

I have presented an improved methodology for estimating local prevalence rates using classical econometric methods. While most of the preceding literature is based on Bayesian methods, my suggested improvements have natural counterparts in a Bayesian framework. However, this paper provides no guidance about the choice between using Bayesian vs. classical methods.

Any methodology that relies on estimates from national datasets must either accept on faith that one particular survey is more appropriate than others or confront the issue of large variation across surveys in reported rates for different mental health diagnoses. Since, as an outsider with no vested interest in one screening tool versus another, I have no reason to "believe" in one over others, I view this problem as a critical issue for the field to resolve. Two issues that have been identified here (though in other work as well) are a) the variation within surveys associated with ICD versus DSM coding and b) the significant variation across surveys even when using the same coding scheme.

Conditional on the validity of national survey responses, available data provide precise and statistically significant estimation of models associated with binary measures of mental health diagnoses (whether one has a mental health problem). One also can estimate polychotomous discrete choice models (what specific diagnosis does one have, if any) allowing for covariance in errors. The big advantage of modeling dependence is the resulting estimate of covariance matrix, allowing for statements about comorbidity. However, a) the parameter estimates for individual binary discrete choices versus polychotomous discrete choices are very similar and b) tail probabilities are not consistent with a joint normality assumption. Thus, more work is required to investigate better, more flexible specifications of the joint density of the errors.

Focusing on binary discrete measures, empirical results from NCS-R and NSADMHP are qualitatively similar though very different from NHIS. I speculate that, to a significant degree, this occurs because both NCS-R and NSADMHP rely on popular screening tools to mechanically diagnosis sample participants, while NHIS relies on self-diagnosis. If I am correct, then, to some degree, we might interpret the difference between the two as a statement about severity of the problem.

Another critical issue is the effects of the precision of local prevalence estimates caused by unobserved community-specific effects. Based on results from CTS and Stern et al. (2009), unobserved community-specific effects have large variance for some diagnoses such as depression and small variance for other measures such as MCS-12. The literature needs to either find ways to reduce the variance of such effects or find ways to measure the variance of such effects associated with specific measures. Using sampling information available

in most national surveys is a good way to proceed. More generally, the lack of precision due to variation in prevalence rates across national surveys and due to potentially large variances of unobserved community-specific effects lead to local prevalence estimates with very wide confidence bands.

Despite the size of confidence bands implied by these two problems, in many cases, one can still make strong policy statements with confidence. Such an example is the public provision of mental health services in central Virginia; the results document a severe shortage of services for people who are unlikely to be able to afford services in the private market.

One could extend the methodology presented in this paper in a number of different directions. One could perform analyses comparing different surveys to allow for better understanding of how to interpret variation in measurement. Such an exercise probably requires the expertise of someone other than an economist. One also could experiment with observable community-specific variables to include as explanatory variables. However, Stern et al. (2009) already control for a large set of such variables implying pessimism about chance of success in reducing the variance of community-specific effects. An alternative way to reduce the variance of unobserved community-specific effects is to include local geographical information in national surveys, thus allowing for a direct estimate of such effects at least for communities represented in the surveys. If such information became available, it would be worthwhile considering ways to allow for spatial correlation to deal with communities not directly represented in the national survey. Finally, one might want to perform more ambitious experiments using the methodology. For example, one might compare prevalence versus need across CSBs (or MSAs) in Virginia or other states and consider how to use such estimates to make better resource allocation decisions.

8 Appendices

8.1 Appendix A: NHIS (1995) Mental Health Questions

Table A1: National Health Interview Survey Mental Health Variable Construction

Mental Health Problem	Question #s	Definition
Anxiety	901	Frequently Depressed or Anxious
Schizophrenia	909	Have Schizophrenia in Past 12 Months
Paranoia	930	Have Paranoid Disorder in Past 12 Months
Bipolar	951	Have Bipolar Disorder in Past 12 Months
Depression	905, 972	Have Serious Trouble Coping with Day-to-Day Stresses (905); Have Major Depression Lasting 2 or More Weeks in Past 12 Months (972)
Personality Disorder	902, 903, 993	Have a Lot of Trouble Making or Keeping Friendships (902); Have a Lot of Trouble Getting Along in Social Setting (903); Have Antisocial Personality, Obsessive Compulsive Personality or Other Personality Disorder in Past 12 Months
Dementia	1014	Have Alzheimer's or Other Senility Disorder in Past 12 Months
Substance Abuse	1035, 1056	Have Alcohol Abuse Disorder in Past 12 Months (1035); Have Drug Abuse Disorder in Past 12 Months (1056)
Other Mental Health Problem	907, 1077	Have Phobias or Unreasonable Fears (907); Have Any Other Mental/Emotional Disorder in Past 12 Months (1077)

8.2 Appendix B: NCS-R Mental Health Questions

Mental Health Definitions for NCS-R				
	DSM		ICD	
	Variable Name	Definition	Variable Name	Definition
depression/ dsythymia	D_DYS12	DSM-IV Dysthymia (12 month)	I_DYS12	ICD Dysthymia (12 month)
	D_DYSH12	DSM-IV Dysthymia w/hierarchy (12 month)	I_DYSH12	ICD Dysthymia with hierarchy (12 month)
	D_MDDH12	DSM-IV Major Depressive Disorder w/ hierarchy (12Mo)	I_MDE12	ICD Severe Depressive Episode (12 month)
	D_MDE12	DSM-IV Major Depressive Episode (12Mo)	I_MDEH12	ICD Severe Depressive Episode w/ hierarchy (12Mo)
anxiety disorders	D_GAD12	DSM-IV Generalized Anxiety Disorder (12Mo)		
	D_GADH12	DSM-IV Gen Anxiety Disorder w/hierarchy (12Mo)		
phobia disorders	D_AGO12	DSM-IV Agoraphobia without Panic Disorder (12Mo)	I_AGP12	ICD Agoraphobia with Panic Disorder (12Mo)
	D_AGP12	DSM-IV Agoraphobia with Panic Disorder (12Mo)	I_SO12	ICD Social Phobia (12 month)
	D_ASA12	DSM-IV Adult Separation Anxiety Disorder (12Mo)	I_SP12	ICD Specific Phobia (12 month)
	D_SO12	DSM-IV Social Phobia (12 month)		
	D_SP12	DSM-IV Specific Phobia (12 month)		
bipolar disorders	D_BIPOLARI12	DSM-IV Bi-polar I (12Mo)	I_HYP12	ICD Hypomania (12 month)
	D_BIPOLARII12	DSM-IV Bi-polar II (12Mo)	I_MAN12	ICD Mania (12 month)
	D_BIPOLARSUB12	DSM-IV Bi-Polar Subthreshold (12Mo)		
	D_HYP12	DSM-IV Hypomania (12 month)		
	D_MDDH12	DSM-IV Major Depressive Disorder w/ hierarchy (12Mo)		
panic disorders	D_PAT12	DSM-IV Panic Attack (12 month)	I_PAT12	ICD Panic Attack (12 month)
	D_PDS12	DSM-IV Panic Disorder (12 month)	I_PDS12	ICD Panic Disorder (12 month)
	D_PTS12	DSM-IV Posttraumatic Stress Disorder (12Mo)		
personality disorders	D_CD12	DSM-IV Conduct Disorder (12 month)	I_CD12	ICD Conduct Disorder (12 month)
	D_IED12	DSM-IV Intermittent Explosive Disorder (12Mo)	I_CDH12	ICD Conduct Disorder w/ hierarchy (12Mo)
	D_IEDH12	DSM-IV Intermittent Explosive Disorder w/ hierarchy (12Mo)	I_ODD12	ICD Oppositional Defiant Disorder (12Mo)
	D_ODD12	DSM-IV Oppositional Defiant Disorder (12Mo)		
	D_ODDH12	DSM-IV OppositionI Defiant Disorder w/ hierarchy (12Mo)		
alcohol abuse	D_ALA12	DSM-IV Alcohol Abuse (12Mo)	I_ALA12	ICD Alcohol Abuse (12 month)
	D_ALAH12	DSM-IV Alcohol Abuse w/ hierarchy (12Mo)	I_ALAH12	ICD Alcohol Abuse w/ hierarchy (12Mo)
	D_ALD12	DSM-IV Alcohol Dependence (12 month)	I_ALD12	ICD Alcohol Dependence (12 month)
drug abuse	D_DRA12	DSM-IV Drug Abuse (12 month)	I_DRA12	ICD Drug Abuse (12 month)
	D_DRAH12	DSM-IV Drug Abuse w/ hierarchy (12 month)	I_DRD12	ICD Drug Dependence (12 month)
	D_DRD12	DSM-IV Drug Dependence (12 month)		
eating disorders	D_ANO12	DSM-IV Anorexia (12Mo)	I_ANOH12	ICD Bulimia (12Mo)
	D_BINGEH12	DSM-IV Binge Eating Disorder w/ hierarchy (12Mo)	I_ANO30	ICD Anorexia (30Day)
	D_BINGEANY12	DSM-IV Binge Any (12Mo)		
	D_BUL12	DSM-IV Bulimia (12Mo)		
	D_BULH12	DSM-IV Bulimia w/ hierarchy (12Mo)		

Note: Variable names and definitions come from Alegria et al. (2008).

8.3 Appendix C: NSADMHP Mental Health Questions

Table A3: NSADMHP Mental Health Variable Construction

	Question #	Definition
Anxiety (DSM)	123	Meet GAD criteria
Major Depressive Episode (DSM)	153	Meet major depression criteria
Dysthymia (DSM)	163	Meet dysthymia criteria
Psychosis (DSM)	167	Psychotic
Panic Disorder (DSM)	174	Panic w/in 12 mos
Panic Disorder (CIDI)	176	Panic, new definition
Substance Abuse	188	Problem drinking (AUDIT score>=8)
	208	Problem with drugs

Note: Question #s and definitions come from Wells, Sturm, and Burnam (2005), Appendix D2.

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