Ohio Family Health Survey

Using Small-Area Estimation Techniques for County-level Estimates of Select Indicators from the Ohio Family Health Survey (2008)

Anirudh V.S. Ruhil
Holly Raffle
Sara Boyd
Nicole R. Yandell

OHIO UNIVERSITY
Voinovich School of Leadership and Public Affairs

OFHS

About the Ohio Family Health Survey

With more than 51,000 households interviewed, the Ohio Family Health Survey is one of the largest and most comprehensive state-level health and insurance surveys conducted in the country. The project was managed by The Ohio State University's Ohio Colleges of Medicine Government Resource Center, and the Health Policy Institute of Ohio and the survey was conducted by Macro International. The Ohio Departments of Insurance, Job and Family Services, Health, and Mental Health, the Cleveland State University, and the Ohio Board of Regents funded the project. This current project is the third in a series of statewide health surveys, following family health surveys in 1998 and 2004.

Ohio Family Health Survey Web site (all sponsored research reports are available for download here):

http://grc.osu.edu/ofhs

Acknowledgments

- Barry Jamieson, MA
- Tim Sahr, MPH, MDiv, ThM, MA
- Amy Ferketich, Ph.D.
- Bo Lu, Ph.D.
- Hope McGonigle, Ph.D

Using Small-Area Estimation Techniques for County-level Estimates of Select Indicators from the Ohio Family Health Survey (2008)

Abstract

Financial and logistical constraints invariably prevent national and state surveys of health behaviors or characteristics from surveying populations of all counties, places, or other sub-national/sub-state geographies (for example, city neighborhoods). However, policy or programmatic considerations often require that reliable estimates be available for these smaller geographies. Small area estimation (SAE) techniques provide one means of deriving estimates for smaller geographies that are undersampled (or not sampled at all) in national/state surveys. In this report we both provide an overview of SAE techniques and test their applicability vis-a-vis the 2008 Ohio Family Health Survey data in the context of generating county-level estimates for particular substantive health status indicators.

Anirudh V.S. Ruhil
Holly Raffle
Sara Boyd
Nicole R. Yandell

The Voinovich School of Leadership & Public Policy
Ohio University
Building 21, The Ridges
Athens, OH 45701-29279
Tel: 740-597-1949 | Fax: 740-597-3057

Small-Area Estimation and the OFHS

> An unbiased estimate is obtained from a sample survey for a large area; when this estimate is used to derive estimates for subareas under the assumptions that the small areas have the same characteristics as the large area, we identify these estimates as synthetic estimates.
> Gonzalez (1973)[1]

Financial and logistical constraints invariably prevent national and state surveys of health behaviors or characteristics from surveying populations of all counties, places, or other sub-national/sub-state geographies (for example, city neighborhoods). However, policy or programmatic considerations often require that reliable estimates be available for these smaller geographies. Small area estimation (SAE) methodologies allow for robust variants of these estimates to be derived from the individual-level national/state survey data supplemented with area-level Census (or other comparable) data.

For example, the sampling design of the 2004 Ohio Family Health Survey (OFHS) placed counties with similar demographic characteristics into four strata - (i) Metropolitan, (ii) Suburban, (iii) Rural Non-Appalachian, and (iv) Rural Appalachian. Further, while the six largest metropolitan counties were to stand alone as individual clusters, the remaining counties were to be grouped, based on demographic similarities, into smaller clusters. The sampling plan for the 2008 OFHS differed somewhat in that the sample was stratified by county, with larger metropolitan areas in the state set as strata in their own right. Despite these variations in sampling plans, the smaller clusters in each survey were expected to, and in many instances did, generate low counts of respondents. These low counts would typically prevent derivation of robust estimates of health behaviors or characteristics based on survey data alone. Synthetic estimation techniques are designed to remedy this very shortcoming by allowing the sparse individual-level survey data from these counties to be used in conjunction with independent county-level data of population characteristics (for example, age, gender, poverty status, etc) to generate robust county-level estimates. Given the need for robust profiles of adults' leading health indicators for the twenty-nine Appalachian counties that comprise the Voinovich School's service region, we chose to employ small area estimation techniques.[2]

Stated most briefly, the analysis proceeds as follows. First, we survey the extant literature with an eye on understanding the nuances of the varying small area estimation techniques commonly encountered in the field. Second, we turn to the 2008 OFHS data to estimate county-level (a) synthetic estimates, (b) generalized linear latent and mixed models (gllamm) estimates, (c) mixed-effects logit estimates, and (d) spatially smoothed variants of the mixed-effects logit estimates.

A Survey of Small-Area Estimation Techniques

There are a number of methods available for small-area estimation, ranging from model-free standardization to complex model-based estimators. Typically these estimators are grouped into three sets – (i) *direct* estimates, derived without any modeling from the area-level data, (ii) *synthetic* or *indirect* estimates, derived on the basis of some regression-type modeling, and (iii) *composite*, derived by combining direct and indirect estimates. Here we focus almost exclusively on direct and indirect estimates.

[1] Gonzalez, M.E. (1973). "Use and Evaluation of Synthetic Estimates." In *Proceedings of the Social Statistics Section* 33-36, American Statistical Association, Washington DC.

[2] Note that Ashtabula, Mahoning, and Trumbull were granted Appalachian status after the 2008 OFHS had been deployed and hence are not treated as Appalachian for purposes of this report.

1. **The Direct Estimate**

   The most common direct estimate is the usual survey-weighted responses for each small-area under consideration. With a sufficient sample size in each areal unit, the good design properties of survey estimators yields unbiased estimates of health behavior with valid confidence intervals.

2. **The Basic Synthetic Estimate** This technique involves applying aggregate estimates of behavior or characteristic of Y (for example, diabetes) derived from the survey data to small-area population counts. For example, the 2008 OFHS survey data show the following diabetes prevalence rates in Ohio for the population 18 years old or older.

   Table 1: Diabetes Prevalence Rates (by Sex)

Sex	Proportion	S.E.	Lower 95% CI	Upper 95% CI
Male	0.1079	0.0029	0.1022	0.1135
Female	0.1201	0.0025	0.1152	0.1251

   One could then assume that similar diabetes prevalence rates would apply for the men and women in each county, and multiplying the rate by the county-specific population size of men and women obtain the number of men and women with self-reported diabetes. In other words, we would proceed by

   (a) Grouping respondents according to some attribute (i.e., sex, age, etc.)
   (b) Grouping respondents by county of residence
   (c) Computing sub-group (i.e., age, sex, etc.) specific rates of diabetes
   (d) For each county, multiplying the appropriate rate for each sub-group by the corresponding population count to obtain expected count of individuals with diabetes
   (e) Dividing the expected counts by the total population count to obtain an estimate of diabetes prevalence within each county

   Although intuitive in its approach and simple in terms of implementation, this method has obvious flaws: The assumption that prevalence of Y does not differ across large and small areas is invariably unwarranted, especially since contextual factors (for example, the environment, economic conditions, and quality of life) vary across geographies more often than not. In fact the assumption driving model-free synthetic estimates invalidates the need for anything but a national survey since all subnational areas can here be assumed equal. But we know this to be patently false.

3. **Synthetic Estimates Using Individual-level Data**

   With this model the individual-level survey data are used to derive a model-based probability of observing Y given a set of covariates (for example, age, gender, etc.). These person-level probability estimates are then converted into estimated proportions of Y within subgroups comprised of each in-sample combination of covariate values. Proportions so estimated are then applied to identical area-level subgroups constructed from population counts. While an improvement over indirect standardization, this technique does not allow contextual variation to play a role in prevalence. This model is fit sequentially as follows:

(a) Group the respondents into defined sub-group (i.e., by age, sex, etc.)

(b) Fit model of individual diabetes incidence using county-level variables and a categorical variable representing the sub-groups

(c) Use model parameters to estimate proportion of individuals with diabetes in each of the sub-groups in each county

(d) Multiply the appropriate subgroup probability by the corresponding county count to estimate the total number of diabetics in each group

(e) Add these estimates over the sub-groups to obtain an overall estimate of the number of diabetics in the county

(f) To estimate diabetes prevalence divide the estimated number of diabetics in the county by the county population count

(g) Obtain the 95 percent credible intervals via Monte Carlo Markov Chain (MCMC)

4. **Synthetic Estimates Using Area-level Covariates**

   Ignoring individual-level covariates, this technique models the prevalence of Y for individuals surveyed in each area as a function of area-specific covariate values. The resulting estimates are thus average estimates for the area in question in that they are the predicted mean prevalence of Y, and vary across areas. Parameter estimates so obtained are then applied to the means or proportions of area covariates constructed from population counts to obtain the desired synthetic estimates.

   (a) Fit model of individual diabetes incidence using area-level covariates

   (b) Apply parameter estimates from the model to corresponding county-level measures to obtain estimate of prevalence of smoking for adults

   (c) Obtain the 95 percent credible intervals via MCMC

5. **Synthetic Estimates Using Both Individual- and Area-level Data**

   More generally known as mixed models, multilevel models, or random coefficients models, these techniques allow the estimated prevalence rates to vary across the small areas. Technically speaking, these models decompose the variation in the prevalence rate of Y across covariates and area-specific fixed and random effects.

   This technique has a number of analytic strengths. For example, insofar as area-specific context matters for health behaviors and their consequences, these models allow contextual factors to influence model estimates. They do so by explicitly recognizing the natural clustering of individuals in each area of interest. Further, multilevel models often provide increased accuracy of standard errors, confidence intervals, and significance tests than if the natural clustering of individuals within specific geographies were ignored.

   That said, there are several hurdles to reliably estimating these models. For one, covariate selection depends upon reasonable overlap in measured covariates in both the survey and the population data. This is usually problematic and hence analysts are forced to use a minimal set of covariates, typically restricted to age, gender, income, etc. If substantively important covariates are excluded from the models because of their unavailability at the individual- and/or area-level, the precision of estimates, standard errors, confidence intervals, and significance tests will be compromised.

In addition, large scale survey data are often drawn collected via particular sampling designs that necessitate the weighting of the resulting survey data prior to analysis and inference. However, including weights in mixed models with dichotomous response variables is a difficult exercise (see Rodriguez and Goldman, 1995, 2001; Rabe-Hesketh and Skrondal 2006).[3] Specifically, the scaling of the level 1 weights strongly influences the variance components, and especially so the variance of the random intercept. The impact is most penal for small cluster sizes, in which case not only the random-intercept but also the regression coefficients reflect bias. The solution appears to be to rescale the regression coefficients as per the random-intercept variance to minimize bias in the estimated marginal effects.

6. **Composite Estimators**

   A number of alternative estimators are available as well. Generalised regression synthetic estimators (GREG) are the most commonly encountered estimators in this class, and adjust survey based prevalence estimates of Y by accounting for numerical differences between the survey and population area means of the relevant predictor. For example, if the survey estimate of mean household size for County A is higher (or lower) than its known average then the estimate of Y for County A is adjusted downwards (or upwards) to account for this difference.

   Composite estimators work towards balancing the design-biased model based estimators against the larger variance of the design-unbiased, direct survey based estimates. One means of doing so is to use a weighted average of the two estimators. Thus, one could take an average of the GREG estimator and a model-based estimate.

7. **Recent Developments in Synthetic Estimators**

   More recently there have been other, more computationally-demanding models proposed in the literature. While almost without exclusion these estimators build on developments in generalized linear latent models (mixed or otherwise), they differ in terms of how they deal with the variances of the random effects. Because these variances are unknown in practice, empirical best linear unbiased predictors (EBLUPs), empirical Bayes (EB), and Hierarchical Bayes (HB) estimation and inference techniques have come to be utilized. Rao (2003) and Malec and Muller (2008) provide excellent overviews of these techniques.[4]

Applying Select Small-Area Estimation Techniques to the 2008 OFHS

A key motivation underlying the 2008 Ohio Family Health Survey (OFHS) was to provide data comparable to the 2004 OFHS data for trend and "change over time" analysis. The 2008 OFHS was also intended to help policy-makers assess the impact of recent changes in the health care market place and government programs, such as Medicaid eligibility expansions. The OFHS would also help policy-makers evaluate the claims that individuals or groups make about continuing needs,

[3] Rodriguez , German and Noreen Goldman. 1995. "An Assessment of Estimation Procedures for Multilevel Models with Binary Responses." *Journal of the Royal Statistical Society. Series A*, 158:73-89; Rodriguez, German and Noreen Goldman. 2001. "Improved Estimation Procedures for Multilevel Models with Binary Response: A Case-Study." *Journal of the Royal Statistical Society. Series A*, 164:339-355; Rabe-Hesketh, Sophia and Anders Skrondal. 2006. "Multilevel Modelling of Complex Survey Data." *Journal of the Royal Statistical Society, Series A* 169:805-827.

[4] Rao, J. N. K. 2003. *Small Area Estimation.* Hoboken, NJ: Wiley; Malec, Donald and Peter Muller. 2008. "A Bayesian Semi-parametric Model for Small Area Estimation." *IMS Collections: Pushing the Limits of Contemporary Statistics in Honor of Jayanta K. Ghosh*, 3:223-236.

problems and solutions. Given these laudable goals, the 2008 OFHS targeted the following population subgroups (see Table 2) in order to generate reliable total statewide estimates of particular health behaviors and outcomes.

Table 2: Sub-Groups of Analytic Interest in the 2008 OFHS Survey

Category	**All**	**Minority Groups**		
		African-American	Hispanic	Asian
Gender	Both	Both	Both	Both
Age	0-17 18-34 35-54 55-64 65+	0-17 18+	0-17 18+	0-17 18+
Family Income*	$\leq$ 100% 101 to $\leq$ 150% 151 to $\leq$ 200% 201 to $\leq$ 250% 251 to $\leq$ 300% 301 to $\leq$ 400% $>$ 400%	$\leq$ 100% 101 to $\leq$ 200% 201 to $\leq$ 300% 301 to $\leq$ 400% $>$ 400%		
Region	Metropolitan Rural Appalachian Non-rural Appalachian Suburban	Each of the 6 largest Metro counties		

* Family income is measured in terms of Federal poverty level, and in particular, the level at which a family is considered to be living in poverty, accounting for family size.

Because the primary purpose of the 2008 OFHS was to provide Ohio policy-makers with information about the health insurance coverage, health status, health care utilization, and health care access of Ohioans per se, the survey was not designed to yield direct survey-based estimates of health behaviors or status indicators for each of the Ohio counties. In fact, the 2008 OFHS sampling plan was such that the necessary clustering of counties (necessary, that is, to obtain reliable county-level health insurance status estimates of children for all 88 counties in Ohio – a key goal of the survey) would restrict the sampling error for the estimate of insurance status to be no greater than $\pm 5\%$ at the 95% level of confidence for the domains listed in Table 2 (see above).

These design considerations *a priori* limited the extent to which information contained within the 2008 OFHS survey response could be directly used to infer the health status and behaviors of adult residents of the 29 Appalachian counties.[5] This is not a problem unique to the 2008 OFHS but in fact invariably encountered when cost and other resource constraints force the survey at issue

[5] By some accounts, at minimum one needs $N = 400$ at the subarea level in order to obtain reliable subarea-level direct estimates (see Jia et al. 2004:457). See Jia, Haomiao, Peter Muennig, and Elaine Borawski. 2004. "Comparison of Small-Area Analysis Techniques for estimating County-Level Outcomes." *American Journal of Preventive Medicine* 26(5):453-460.

to be designed with large population groups (or subgroups therein) in mind. In these situations, statistical, model-based estimates of health indicators of interest can nevertheless be derived.

Given the generally limited availability of health data for the Appalachian counties and the perennial need for statistically defensible estimates of health data useful for crafting policy, shaping programmatic decisions, and soliciting funding for rural health research, we had sought OFHS funding to generate the needed estimates for Appalachian counties via appropriate small area estimation techniques. In particular, we intended to employ parametric, hierarchical models for small area estimation developed by Malec et al. (1997).[6] These models have been employed in diverse research applications in the health sector, ranging from real-time county-level monitoring of influenza vaccination coverage during the 2004-2005 influenza season (Jia et al 2006)[7] to estimates of mammography use in the states (Legler et al 2002)[8] and, most recently, to county-level estimates of diagnosed diabetes in the United States.[9]

The general modeling strategy employed by these studies involves fitting binary dependent variable models to the survey data at hand, within a hierarchical regression framework. In particular, given a vector of t covariates, $x_{ij} = (x_{ij1}, x_{ij2}, \cdots, x_{ijt})'$ for the survey respondents and corresponding fixed-effects $\beta = (\beta_1, \beta_2, \cdots, \beta_t)'$, we will estimate a multilevel logistic regression model for each health behavior or status indicator identified in this proposal: $logit(p_{ij}) = x_{ij}^{'}\beta + \alpha_i$ where α_i represent county-level random effects $\sim$ iid $Normal(0, \sigma^2)$. The covariate vector x typically includes data measured at two levels – the respondent's demographic and socioeconomic indicators available from the 2008 OFHS (currently known to be gender, age, income, and race), and selected county-level socioeconomic and demographic measures drawn from data available through the Bureau of the Census and/or state databases.

Rephrasing the preceding discussion in non-technical terms, the analysis proceeds as follows:

1. Regress survey data on Y against selected covariates.

2. Attach parameter estimates to the similar area-level covariates for *each* area in the population to generate a *predicted* value of Y for each area

3. Generate the desired confidence intervals using the estimated variance of the random effects. In particular, Wald-type intervals can be approximated for county k as, for example, the 95% CI is

$$\tilde{\zeta}_k^2 \pm 1.96SE\left(\tilde{\zeta}_k^2\right)$$

   where $\tilde{\zeta}_k^2$ is the estimated level 2 (i.e., county) random intercept for county k

4. If the interest is also in reporting the estimated parameters and their confidence intervals (whether in base or odds-ratio forms), then one may simple compute

$$\hat{\beta} \pm z_{0.975}\hat{SE}\left(\hat{\beta}\right)$$

[6] Malec, Donald, J. Sedransk, Christopher L. Moriarity, and Felicia B. LeClere. 1997. "Small Area Inference for Binary Variables in the National health Interview Survey." *Journal of the American Statistical Association* 92(439):815-826.

[7] Jia, Haomiao, Michael Link, James Holt, Ali H. Mokdad, Lei Li, and Paul S. Levy. 2006. "Monitoring County-Level Vaccination Coverage During the 2004-2005 Influenza Season." *American Journal of Preventive Medicine* 31(4):275-280

[8] Legler J, H. I. Meissner, C. Coyne, N. Breen, V. Chollette, and B. K. Rimer. 2002. "The Effectiveness of Interventions to Promote Mammography Among Women with Historically Lower Rates of Screening." *Cancer Epidemiology Biomarkers and Prevention* 11(1):59-71.

[9] Centers for Disease Control and Prevention: National Diabetes Surveillance System. Available online at: `http://www.cdc.gov/diabetes/statistics/index.htm`. Retrieved 7/21/2008.

or

$$exp\left\{\hat{\beta} \pm z_{0.975}\hat{SE}\left(\hat{\beta}\right)\right\}$$

This technique has a number of analytic strengths. For example, insofar as area-specific context matters for health behaviors and their consequences, these models allow contextual factors to influence model estimates. They do so by explicitly recognizing the natural clustering of individuals in each area of interest. Further, multilevel models often provide increased accuracy of standard errors, confidence intervals, and significance tests than if the natural clustering of individuals within specific geographies were ignored. "The multilevel approach is also relatively robust to variations in the number of observations in each sampling unit; model estimates based on relatively few observations are weighted towards the global average for the data" (Twigg and Moon 2002).[10] This is a particularly useful property (familiar to multilevel modelers as "shrinkage") of these estimators given the thin cells likely for some counties (see Table 3).

Table 3: 2003-2004 OFHS Sample Disposition by Appalachian Cluster

Demographic	Appalachian Cluster	Minimum	Maximum
Gender			
Male	4,112	67	370
Female	7,319	152	690
Total	11,431		
Age			
18-24	466	5	39
25-34	1,141	17	114
35-44	1,744	29	194
45-54	2,331	41	237
55-64	2,463	41	209
65 +	3,289	67	267
Total	11,431		
Income			
$< 100\%$	2,266	49	150
$101 - 150\%$	1,608	28	104
$151 - 200\%$	1,269	18	84
$201 - 300\%$	2,287	47	206
301%+	4,004	58	516
Total	11,431		
Imputed Race			
White/Other	10,980	227	1,012
Black/African-American	172	0	12
Hispanic	242	2	28
Asian	40	59	775
Total	11,434		

[10] L. Twigg and G. Moon. 2002. "Predicting Small Area Health-related Behaviour: A Comparison of Multilevel Synthetic Estimation and Local Survey Data." *Social Science and Medicine* 54(6):931-937.

That said, there are several hurdles to reliably estimating these models. For one, covariate selection depends upon the availability of similarly measured covariates in both the survey and the population data. This is usually problematic and hence analysts are forced to use a minimal set of covariates, typically restricted to the usual demographic/socioeconomic suspects (for example, age, gender, income, educational attainment, etc). If substantively important covariates (that is, individual- or area-level covariates known to influence Y) are excluded from the models because of their unavailability at the individual- and/or area-level, parameter estimates will be imprecise. In addition, pooling data from multiple surveys is often preferable to using a single survey because of the resulting improved coverage of areal units this generates.

The Estimation Sequence

Prior to all analyses we merged the 2008 OFHS survey data with the county-level estimates (for 2007) of sex, age, race, and poverty from the the U.S. Bureau of the Census' publicly available database.[11] The goal here was to create county-level analogues of the basic demographic indicators recorded by the 2008 OFHS. Given the lack of racial/ethnic diversity in the Appalachian counties, it was decided to exclude racial/ethnic indicators from all analyses.

Our substantive focus was on respondents' answers to the following questions:

High Blood Pressure

d41 Have you/Has [FILL IN] ever been told by a doctor or any other health professional that you/he/she had high blood pressure or hypertension?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

Heart Attack

d41a Has a doctor, nurse, or other health professional EVER told you/[FILL IN] that you/he/she had any of the following? A heart attack, also called a myocardial infarction?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

Coronary Heart Disease

d41b Has a doctor, nurse, or other health professional EVER told you/[FILL IN] that you/he/she had any of the following? Coronary heart disease also known as coronary ARTERY disease, congestive heart disease, angina?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

Stroke

d41c Has a doctor, nurse, or other health professional EVER told you/[FILL IN] that you/he/she had any of the following? A stroke?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

[11] See `http://www.census.gov/popest/counties/`.

Congestive Heart Failure

d41d Has a doctor, nurse, or other health professional EVER told you/[FILL IN] that you/he/she had any of the following? Congestive heart failure?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as yes 02, 98, and 99 coded as no

Diabetes

d43 Have you/Has [FILL IN] ever been told by a doctor or any other health professional that you/he/she had diabetes or sugar diabetes?

01-YES 02-NO 03-BORDERLINE 98-DK 99-REFUSED

01- Coded as "Yes" 02, 03, 98, and 99 coded as "No"

Cancer

d47 Have you/Has [FILL IN] ever been told by a doctor that you/he/she had CANCER of any type?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

Obesity

bmi_a_cat BMI category - adult

01-UNDERWEIGHT 02-NORMAL OR HEALTHY WEIGHT 03-OVERWEIGHT 04-OBESE 05-BMI/age out of range: BMI_C_PCT/BMI_C_Z not computed

01- Coded as "Yes" 02, 03, 04 coded as "No" 05 omitted

Need Rx

f68b IN THE PAST 12 MONTHS, have you/has [FILL IN] NOT filled a prescription because of the cost?

01-YES 02-NO 98-DK 99-REFUSED

01- Coded as "Yes" 02, 98, and 99 coded as "No"

Pay Bills

f70 DURING THE LAST 12 MONTHS, were there times when you/[FILL IN] had problems paying or you were/[FILL IN] was unable to pay for medical bills for yourself/himself/herself or anyone else?

01-YES 02-NO 98-DK 99-REFUSED 01- Coded as "Yes" 02, 98, and 99 coded as "No"

Note that although we had initially included questions f70b1, f70b2, and f70b3 for analysis, the skip patterns applicable to these questions led to sample sizes that were insufficient for our estimation purposes.[12] Consequently we decided to exclude these three questions from all analyses.

[12] Questions f70b1, f70b2, and f70b3 asked: "Have any of the following happened because you/[FILL IN] had to pay medical bills?" with the specific events referring to *been unable to pay for basic necessities like food, heat or rent* (f70b1), *used up all or most of savings* (f70b2), and *had large credit card debt OR had to take a loan or debt against [the home] OR had to take any kind of loan* (f70b3).

The Basic Synthetic Method

The first set of estimates were generated via the synthetic method. In particular, we began by constructing interactions between sex and age to identify particular demographic categories j_i such that j_1 identified indicated Male respondents in the 18-24 age-group, j_2 identified Male respondents in the 25-34 age-group, and so on through j_12 which identified Female respondents in the 65+ age-group. For each j_i we next estimated $\hat{p}_{.j}$, the (weighted) state prevalence rate. Using diabetes as an example, this led to the weighted state prevalence rates enumerated in Table 4 below.

Table 4: Diabetes Prevalence Rates (by Sex and Age Group)

Sex × Age	Proportion ($\hat{p}_{.j}$)	S.E.	Lower 95% CI	Upper 95% CI
Males 18-24	0.0105	0.0036	0.0033	0.0176
Males 25-34	0.0278	0.0046	0.0188	0.0368
Males 35-44	0.0586	0.0055	0.0478	0.0694
Males 45-54	0.1014	0.0064	0.0889	0.1139
Males 55-64	0.1913	0.0085	0.1746	0.2081
Males 65+	0.2581	0.0095	0.2394	0.2768
Females 18-24	0.0352	0.0061	0.0232	0.0471
Females 25-34	0.0599	0.0055	0.0491	0.0707
Females 35-44	0.0784	0.0052	0.0683	0.0886
Females 45-54	0.1023	0.0054	0.0916	0.1129
Females 55-64	0.1776	0.0068	0.1642	0.1910
Females 65+	0.2256	0.0065	0.2128	0.2383

Thereafter we calculated the synthetic estimate of the diabetes rate for county i as:

$$\hat{p}_i = \sum_j \frac{n_{ij}}{n_i} \hat{p}_{.j}$$

Note that in the preceding formula n_i refers to the total (adult) population in county i and n_{ij} is the total (adult) population belonging to category j in county i.

The preceding sequence was repeated for each substantive variable of interest, and the resulting county-level estimates are given in Tables 5 through 15.

GLLAMM and Mixed-effects Logit Synthetic Estimates

We next turned to deriving model-based estimates via the following routines. We estimated the following random-effects logistic regression: $logit(p_{ij}) = x_{ij}^{'}\beta + \mu_i$ where $x_{ij}^{'}$ corresponded to respondent-level and county-level covariates (age, sex, race, etc.), and the β were corresponding fixed effects. Given n_i, the total population in county i and n_{ij} the total population belonging to category j in county i, county-level prevalence rates were estimated as

$$\hat{p}_i = \sum_j \frac{n_{ij}}{n_i} \hat{p}_{ij}$$

Note that when computing $\hat{p}_{ij}$, we included the random-effect term but excluded individual values of random effects (see also Jia et al. 2006). These estimates (and their associated standard errors are provide in Table A.1 through Table A.10 in the Appendix.

All estimation was conducted using two routines for random-effects logit models available in Stata 10.1 – *gllamm* and *xtmelogit*. We chose to employ both routines because each has its strengths and weaknesses; *xtmelogit* tends to converge faster than does *gllamm* but *gllamm* is the only Stata 10.1 routine for this class of models that provides empirical Bayes linear unbiased predictions (EBLUPs) postestimation. In the empirical Bayes approach, the prior distribution of these random parameters is used in conjunction with the likelihood to obtain the posterior distribution of these random parameters given the observed response (y_{ij}). It is just the mean of the posterior distribution with the parameter estimates plugged in. Their one shortcoming in that the variance of these EBLUPs does not take into account the uncertainty in the parameter estimates since they are treated as known in order for EBLUP to proceed as usual. By some accounts, EBLUPs underestimate the posterior variances; this is where the Hierarchical Bayes (HB) estimates outperform all other SAE techniques (see Malec et al. 1997:821-22). Therefore, while in theory values can be assigned to the predicted random intercepts, it is recommended that one eschew this application because the distribution of these random parameters is unknown if the model is true (see Rabe-Hesketh and Skrondal (2008) for details).[13] Further, the posterior standard deviation associated with the predicted random intercepts is at best an approximation. Consequently, while we provide predictions and standard errors from both the *gllamm* and the *xtmelogit* estimates, we urge caution in their interpretation. At best, and that assuming no model misspecification or measurement error, the plots of the ranked county-specific random intercepts (and their approximate 90% confidence intervals) shown in Figures 1 through 10 are likely to be most reliable for assessing how the counties fare on a given substantive dimension.[14]

In the *gllamm* formulations, the basic model estimated is a two-level random-effects logit specification that included the following respondent-level covariates – Sex (Female = 1; Male = 0), Age-groups (18-24; 25-34; 35-44; 45-54; 55-64; 65+), Poverty (100% or less; 101%-150%; 151%-200%; 201%-300%; 301%+). We also constructed analogous county-level covariates for Sex and Age via available Census data.

Analyses proceeded via an iterative model-fitting sequence that tested for alternative specifications, including interactions between respondent-level covariates and, in turn, county-level covariates (see Malec et al. 1997). Because both *gllamm* and *xtmelogit* are computationally intensive routines, model-fitting was a very time-consuming process that also frequently led to failed numerical integration of the quadratures, both in the native Windows Stata 10.1 setup as well as in a far more powerful Linux environment running Stata 9.2.

Consequently, we settled for parsimony over complexity and in doing so had to opt for models that did not include the county-level analogues. Indeed, as a matter of fact parameter estimates of county-level indicators (as well as their interactions) were consistently statistically insignificant, and hence we have reasonable faith that excluding these covariates from the final models does not bias the estimates in any particular direction. We surmise that the better than expected coverage of all Ohio counties obtained by the 2008 OFHS – as compared to, for example, by the BRFSS annualized data or by the 2004 OFHS – led the respondent-level indicators to overwhelm the county-level indicators. The final model *gllamm* specifications included indicators for Sex (Female = 1);

[13]Rabe-Hesketh, Sophia and Anders Skrondal. 2008. *Multilevel and Longitudinal Modeling Using Stata*. College Station, TX: Stata Press.

[14]Figures 1 through 10 show how the any given county stacks up against another county, once respondents' sex, age, and poverty status have been controlled for vis-a-vis, for example, their diabetes status. Because these are county-level random intercepts, they tell us something meaningful (within limits of course) depending upon whether, say, County A has a positive or negative intercept. If County A has a positive intercept and County B has a negative intercept, then we know that despite controlling for sex, age, and poverty status residents in County A have a higher likelihood of diabetes (or high blood pressure, etc.) than their peers in County B.

Age (25-34; 35-44; 45-54; 55-64; 65+); and Poverty (101-150%; 151%-200%; 201%-300%; 301%+). The excluded categories were Age = 18-24; and Poverty = $\leq$ 100%. The *xtmelogit* models were essentially unconditional models with county-effects modeled as random effects.

Spatial Smoothing

Spatial smoothing is useful when the goal is to assess spatial patterns of the prevalence or incidence of some disease or non-health attribute (adult literacy, for example). It is useful because invariably sparse sampling underlies the estimated rates, injecting uncertainty into the estimates. As a result various techniques have been proposed to mitigate this uncertainty, and each revolves around deriving a linear or non-linear average of geographically neighboring estimates. Of these techniques, the median-based headbanging algorithm has been used most often in the literature because unlike other smoothers it better preserves the real spatial structure.[15] Spatial smoothing does, however, generate some artifacts, and especially so in the case of corner points and edge points. If one opts for unweighted headbanging, then points with fewer triples are more likely to see artifacts result. As Gelman et al. (2000) emphasize, "Spatial smoothing methods such as headbanging can equalize the variances somewhat, but there is ultimately no way to avoid unequal variances given that data come with unequal sample sizes."[16] One means of assessing how much distortion is being introduced via headbanging is to tabulate how often counties ended up in the same quintile before and after smoothing. See Nandram et al. (2000) for an illustration.[17] Likewise, when Jia et al. (2006) put their estimates through the headbanging algorithm they try to deal with the resulting issue of artefacts (for example, small suburban counties' values being changed to their large metropolitan neighbors' values) by limiting the "before" and "after" change to no more than a 25% difference from the original (i.e., pre-smoothing) values.[18] Time and resource limitations precluded us from conducting any such assessments of the smoothed estimates.

We employed (adult) population weights in the smoothing process so that unusually high or low estimates that could be reliable because of large populations remain unmodified but estimates based on sparse populations were modified to be more like their surrounding counties. In practice, if a county does not have any sampled respondent then researchers typically substitute the state weighted mean estimate for the missing estimates, prior to initiating the smoothing process (see Pickle and Su (2002) for details.[19] However, the 2008 OFHS had sufficient coverage of each county to obviate the need for any such adjustment. It should be noted that while smoothing stabilizes results for sparsely populated areas by borrowing information from neighboring areas, thereby reducing variability in the data and allowing patterns to emerge, it *increases the bias in the estimates for each small area*. Thus the smoothed estimates we report in Tables 5 through 14 should not be

[15] See Mungiole, M, Pickle, L W and Simonson, K H. 1999. "Application of a Weighted Headbanging Algorithm to Mortality Data Maps." *Statistics in Medicine* 18:3201-3209.

[16] Gelman, Andrew, Philip N. Price, and Chia-yu Lin. 2000. "A Method for Quantifying Artefacts in mapping Methods Illustrated by Application to Headbanging." *Statistics in Medicine* 19:2309-2320.

[17] Nandram, B, Sedransk, J and Pickle, L. 2000. "Bayesian Analysis and Mapping of Mortality Rates for Chronic Obstructive Pulmonary Disease." *Journal of the American Statistical Association* 95:1110-1118. See also Mungiole, M. and Linda W. Pickle. (1999). "Determinng the Optimal Degree of Smoothing Using the Weighted Head-banging Algorithm on Mapped Mortality Data." In *ASC '99 – Leading Survey & Statistical Computing into the New Millenium.* Proceedings of the ASC International Conference, September.

[18] Jia, Haomiao, Michael Link, James Holt, Ali H. Mokdad, Lei Li, and Paul S. Levy. 2006. "Monitoring County-Level Vaccination Coverage During the 2004-2005 Influenza Season." *American Journal of Preventive Medicine* 31(4):275-280.

[19] Pickle, Linda Williams and Yuchen Su. 2002. "Within-State Geographic Patterns of Health Insurance Coverage and Health Risk Factors in the United States." *American Journal of Preventive Medicine* 22(2):75-83

interpreted as exact *per se* but rather used to identify and compare clusters with similar values.

We smoothed the xtmelogit estimates (largely as an exploratory exercise) as follows:

1. Find u_i, the Median prevalence rate for all counties that neighbor county i
2. Group these neighboring counties according to whether their estimated prevalence rate (a) exceeds or (b) does not exceed u_i.
3. Define High Screen for County i as Weighted Median prevalence rate of neighboring counties $\geq u_i$
4. Define Low Screen for County i as Weighted Median prevalence rate of neighboring counties $< u_i$
5. Note that weights are based on the county population
6. If Low Screen $\leq \hat{p}_i \leq$ High Screen, then leave $\hat{p}_i$ unchanged.
7. If $\hat{p}_i >$ High Screen, then set $\hat{p}_i =$ High Screen.
8. If $\hat{p}_i <$ Low Screen, then set $\hat{p}_i =$ Low Screen.
9. Repeat the preceding steps 10 times to come up with a moving average.

Again, we urge caution in treating the smoothed estimates as anything more than a medium for exploring similarities amongst the clusters. Although smoothing reduces variability in the data, allowing patterns to emerge, it also increases the bias in the estimate for each small area.

Conclusion

Small-area estimation techniques provide, both in theory and in practice, substantial leverage by way of enabling analysts to generate estimates for smaller geographies (counties, places, neighborhoods) that are often undersampled (or not sampled), in national/state surveys. In this report we have provided a brief overview of these techniques, as well as a demonstration of some basic estimation techniques – both model-free and model-based, with and without spatial smoothing. We did so in the context of the 2008 Ohio Family Health Survey (OFHS). The small area estimates we derived, regardless of modeling options, depart significantly from the unconditional survey-weighted estimates. Given that the survey-weighted estimates are design-unbiased, it would be prudent to regard them as "true" estimates of each of the target response variables. Consequently, we can benchmark all other estimates reported here against the survey-weighted estimates. For the most part, and regardless of the substantive question we focus on, notice for example that the synthetic estimates are on average within $\pm 1 - 2\%$ of the survey-weighted estimates – well within the usual confidence intervals (standard errors of survey-weighted estimates are enumerated in the third column of Tables 5 through 14).

Clearly, if the goal is to generate reliable county-level estimates of diabetes, stroke, cancer, and so on – regardless of the sex or age or poverty-level of sub-populations – from the 2008 OFHS, then we recommend use of the survey-weighted estimates. This is so largely because the 2008 OFHS survey provides good coverage for virtually all counties. Another reason for the discrepancy between the model-based estimates and the direct survey-weighted estimates could be that the predictors used in the model were essentially few to begin with and even then not driven by substantive knowledge of the specific factors known to predict diabetes, obesity, and so forth. When sample coverage of the small areas is sparse, however, as is the case with the BRFSS data, then model-based estimates will by default be preferred because the surveys like the BRFSS do not cover each county in the state. Nor do we incorporate sampling weights into the small area estimates; if model-based estimates are to be used, users must be cognizant of the consequences of folding (or not) survey weights into the analyses. Survey weights may not always be usable given that weighting is an especially thorny issue in the context of hierarchical linear modeling (see Rodriguez and Goldman 2001; Rabe-Hesketh and Skrondal 2006). However, recent attempts to include survey weights in small area estimators shows promise (see Folsom et al. 2008).[20]

Overall, our research suggests that the OFHS makes two vital contributions. First, the OFHS is the only source of county-level information on a host of health status indicators for the state. Indeed, ideally the OFHS would run every two years, if not annually because in doing so public health agencies, policymakers, and researchers would have access to more timely, trend data at the sub-state level. Without this frequency of data, users are forced to rely either upon outdated data (such as the 2004 OFHS until the 2008 OFHS data were released) or then upon small area estimates that are both cumbersome and noisy to obtain from the BRFSS. Second, the 2004 and 2008 OFHS provide a unique opportunity to compare the accuracy of BRFSS-derived county-level estimates for selected health indicators vis-a-vis the direct survey-weighted estimates the OFHS yields. Such comparisons could illustrate the extent to which estimates derived from the various small area estimation techniques applied to BRFSS data (where few counties are sampled in any given state in any given year) approach the "true" values embodied in the OFHS, and when they fail to overlap, the causes for these failures. In our ongoing work we are undertaking this latter inquiry, comparing in particular (i) the model-free synthetic estimates, (ii) the EBLUP approach of the random-intercept mixed logit models, and (iii) the Hierarchical Bayes approach to 2008 OFHS estimates.

The main policy consideration that emerges from our analyses is that local and regional community health agencies and health care providers should use data and information provided from instruments such as the Ohio Family Health Survey to shape policies and programs that address health problems and stressors at regional and local levels. When instruments like the OFHS are unavailable, and the proliferation and ease of modern statistical computing resources notwithstanding, local, regional, and state policymakers and health service providers should consider the pros and cons of employing synthetic, model-based, and spatial techniques to examine their communities.

[20] Folsom, Ralph E., Babubhai Shah, Avinash Singh, Akhil Vaish, Neeraja Sathe, and Lea Truman. 2008. Small Area Estimation to Target High-Risk Populations for Health Intervention. Retrieved from `http://chsr.sph.unc.edu/ResearchProjects/Project3_bottom.htm`

Table 5: Comparing High Blood Pressure Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	33.92%	4.71%	33.26%	46.69%
Allen	394	34.07%	3.05%	33.10%	41.61%
Ashland	323	35.33%	3.75%	33.18%	42.25%
Ashtabula	403	32.72%	2.99%	34.12%	41.94%
Athens	336	33.78%	3.68%	25.26%	42.38%
Auglaize	272	32.58%	3.59%	33.72%	41.61%
Belmont	348	33.65%	3.17%	35.91%	43.04%
Brown	662	40.17%	3.57%	32.01%	45.29%
Butler	1284	30.79%	1.55%	30.26%	40.93%
Carroll	303	39.59%	5.18%	34.43%	41.94%
Champaign	314	35.43%	4.08%	33.18%	40.93%
Clark	407	40.45%	3.02%	34.00%	40.93%
Clermont	1060	34.10%	2.00%	30.53%	40.93%
Clinton	293	36.40%	4.25%	31.71%	43.36%
Columbiana	466	32.44%	2.69%	34.22%	43.36%
Coshocton	376	39.61%	4.03%	34.41%	41.92%
Crawford	291	36.70%	3.94%	34.53%	43.45%
Cuyahoga	4103	33.96%	0.94%	33.84%	42.25%
Darke	469	28.74%	3.21%	34.53%	40.57%
Defiance	337	36.15%	4.08%	33.03%	40.67%
Delaware	335	31.77%	2.91%	29.98%	38.55%
Erie	407	36.31%	3.36%	35.05%	42.25%
Fairfield	288	39.82%	3.30%	32.02%	41.92%
Fayette	279	32.75%	4.05%	33.77%	42.34%
Franklin	3118	32.39%	1.04%	28.86%	38.55%
Fulton	266	30.00%	3.85%	32.95%	42.82%
Gallia	310	36.88%	4.29%	33.19%	45.94%
Geauga	262	28.47%	3.20%	34.10%	41.94%
Greene	350	34.00%	2.81%	31.07%	40.93%
Guernsey	290	35.21%	4.05%	34.17%	43.04%
Hamilton	2266	34.77%	1.22%	32.23%	40.93%
Hancock	396	32.34%	3.09%	32.46%	42.77%
Hardin	280	36.84%	4.47%	31.01%	42.77%
Harrison	262	29.94%	4.06%	36.32%	43.04%
Henry	303	28.09%	3.74%	33.54%	42.82%
Highland	634	34.75%	4.01%	33.47%	43.85%
Hocking	269	39.18%	5.18%	33.54%	46.92%
Holmes	326	23.15%	3.36%	30.82%	40.64%
Huron	402	30.60%	3.23%	32.39%	42.25%
Jackson	307	46.56%	4.97%	33.09%	47.00%
Jefferson	338	36.15%	3.37%	36.20%	43.36%

Continued on next page

Table 5 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	34.92%	3.70%	32.64%	42.13%
Lake	377	34.76%	2.62%	33.76%	41.94%
Lawrence	359	46.96%	3.83%	33.88%	48.98%
Licking	286	30.77%	2.97%	32.35%	38.66%
Logan	296	34.76%	3.85%	33.62%	42.77%
Lorain	1878	33.55%	1.64%	32.52%	42.25%
Lucas	1857	34.32%	1.55%	32.09%	42.82%
Madison	280	39.12%	4.52%	31.24%	39.92%
Mahoning	1324	33.81%	1.82%	35.43%	42.00%
Marion	398	39.27%	3.69%	32.95%	43.45%
Medina	251	35.40%	3.22%	31.98%	41.94%
Meigs	480	36.45%	5.02%	34.19%	47.79%
Mercer	329	25.41%	3.32%	33.92%	40.57%
Miami	332	36.14%	3.19%	33.58%	43.56%
Monroe	232	34.91%	6.45%	35.93%	43.36%
Montgomery	1770	35.81%	1.46%	32.66%	45.40%
Morgan	319	41.29%	7.31%	35.06%	43.04%
Morrow	266	33.41%	4.14%	32.54%	42.89%
Muskingum	337	33.75%	3.27%	33.35%	41.92%
Noble	261	29.50%	4.24%	31.44%	43.04%
Ottawa	316	35.35%	3.66%	35.97%	42.25%
Paulding	320	45.39%	6.11%	32.93%	40.67%
Perry	267	34.87%	4.42%	32.30%	42.13%
Pickaway	282	30.13%	3.61%	31.34%	41.45%
Pike	406	34.79%	4.44%	32.83%	45.92%
Portage	285	38.50%	3.18%	30.06%	41.94%
Preble	354	39.81%	3.79%	33.45%	40.93%
Putnam	306	34.72%	4.10%	32.98%	41.61%
Richland	341	40.57%	3.18%	33.74%	43.45%
Ross	365	36.29%	3.63%	32.21%	41.45%
Sandusky	398	36.31%	3.58%	33.83%	42.82%
Scioto	462	39.57%	3.38%	33.50%	47.00%
Seneca	361	34.33%	3.68%	32.89%	43.45%
Shelby	326	34.42%	4.06%	32.37%	41.61%
Stark	1137	32.74%	1.64%	34.14%	40.64%
Summit	3346	32.55%	1.24%	33.16%	41.94%
Trumbull	617	33.67%	2.23%	34.78%	42.00%
Tuscarawas	556	32.12%	2.78%	34.15%	40.91%
Union	286	27.88%	3.66%	30.15%	40.81%
Van Wert	301	27.98%	4.39%	34.32%	40.67%
Vinton	235	35.02%	5.67%	32.54%	46.92%
Warren	748	27.73%	2.03%	30.46%	40.93%

Continued on next page

Table 5 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	33.02%	3.23%	34.16%	42.38%
Wayne	661	30.73%	2.41%	32.25%	40.64%
Williams	337	26.81%	3.23%	33.49%	40.07%
Wood	687	28.84%	2.22%	29.27%	42.82%
Wyandot	288	36.89%	4.71%	34.29%	42.89%
Total	50944				

Table 6: Comparing Heart Attack Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	8.17%	3.34%	5.26%	8.37%
Allen	394	5.73%	1.32%	5.23%	8.10%
Ashland	323	7.56%	1.95%	5.26%	8.14%
Ashtabula	403	5.80%	1.33%	5.45%	6.75%
Athens	336	5.18%	1.63%	3.59%	8.19%
Auglaize	272	5.00%	1.49%	5.35%	7.27%
Belmont	348	10.32%	1.92%	5.87%	7.44%
Brown	662	6.90%	1.18%	4.91%	8.37%
Butler	1284	4.46%	0.68%	4.50%	5.81%
Carroll	303	2.89%	0.98%	5.52%	6.75%
Champaign	314	5.90%	2.18%	5.14%	7.21%
Clark	407	6.52%	1.51%	5.40%	7.21%
Clermont	1060	4.98%	0.72%	4.46%	7.18%
Clinton	293	9.24%	2.76%	4.84%	7.98%
Columbiana	466	6.29%	1.58%	5.46%	7.13%
Coshocton	376	4.88%	1.21%	5.51%	7.93%
Crawford	291	8.41%	2.07%	5.53%	8.14%
Cuyahoga	4103	4.34%	0.37%	5.38%	6.39%
Darke	469	7.34%	2.00%	5.56%	6.87%
Defiance	337	5.94%	2.13%	5.14%	7.02%
Delaware	335	2.24%	0.92%	4.28%	5.94%
Erie	407	6.00%	1.26%	5.70%	7.39%
Fairfield	288	5.29%	1.52%	4.85%	6.50%
Fayette	279	6.41%	1.77%	5.36%	7.98%
Franklin	3118	4.82%	0.46%	4.13%	5.94%
Fulton	266	4.62%	1.58%	5.13%	7.02%
Gallia	310	7.48%	2.03%	5.21%	8.87%
Geauga	262	2.84%	0.94%	5.32%	6.39%
Greene	350	4.24%	1.16%	4.73%	7.18%
Guernsey	290	4.62%	1.12%	5.46%	8.00%
Hamilton	2266	4.58%	0.51%	4.96%	5.66%
Hancock	396	5.88%	1.15%	5.04%	8.10%
Hardin	280	6.26%	1.63%	4.81%	7.81%
Harrison	262	5.50%	1.43%	6.03%	7.44%
Henry	303	6.31%	2.55%	5.30%	7.40%
Highland	634	9.52%	2.21%	5.31%	9.20%
Hocking	269	5.41%	1.98%	5.34%	7.79%
Holmes	326	7.28%	1.85%	4.73%	8.14%
Huron	402	4.29%	1.02%	5.01%	6.95%
Jackson	307	14.06%	4.15%	5.14%	8.58%
Jefferson	338	5.93%	1.44%	5.99%	7.44%

Continued on next page

Table 6 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	8.76%	2.10%	5.14%	8.14%
Lake	377	5.75%	1.32%	5.30%	6.40%
Lawrence	359	10.86%	2.26%	5.36%	9.58%
Licking	286	3.40%	1.17%	4.95%	5.94%
Logan	296	7.19%	1.85%	5.33%	7.77%
Lorain	1878	4.84%	0.69%	5.02%	6.39%
Lucas	1857	6.57%	0.78%	4.94%	8.21%
Madison	280	8.20%	2.62%	4.68%	6.78%
Mahoning	1324	5.44%	0.84%	5.81%	6.54%
Marion	398	6.31%	1.48%	5.12%	7.87%
Medina	251	2.22%	0.94%	4.81%	6.39%
Meigs	480	5.63%	1.19%	5.45%	9.37%
Mercer	329	6.52%	2.73%	5.47%	7.02%
Miami	332	6.19%	1.65%	5.24%	7.21%
Monroe	232	2.88%	1.04%	5.92%	7.44%
Montgomery	1770	5.58%	0.66%	5.08%	7.56%
Morgan	319	4.43%	1.59%	5.70%	8.19%
Morrow	266	6.17%	1.77%	5.02%	7.50%
Muskingum	337	7.48%	1.68%	5.27%	8.15%
Noble	261	8.05%	2.00%	4.88%	8.19%
Ottawa	316	6.84%	1.80%	5.90%	7.39%
Paulding	320	6.94%	2.01%	5.11%	7.02%
Perry	267	9.43%	3.08%	4.99%	8.15%
Pickaway	282	7.48%	2.02%	4.72%	7.30%
Pike	406	9.09%	2.27%	5.18%	9.20%
Portage	285	5.74%	1.48%	4.52%	6.75%
Preble	354	6.81%	2.26%	5.25%	7.18%
Putnam	306	8.51%	2.05%	5.19%	8.10%
Richland	341	7.01%	1.58%	5.33%	8.14%
Ross	365	7.39%	2.20%	4.93%	7.30%
Sandusky	398	5.04%	1.14%	5.37%	8.21%
Scioto	462	8.72%	1.97%	5.30%	9.20%
Seneca	361	5.56%	1.84%	5.21%	8.21%
Shelby	326	4.30%	1.11%	4.99%	7.56%
Stark	1137	5.37%	0.77%	5.44%	6.75%
Summit	3346	3.95%	0.47%	5.19%	6.39%
Trumbull	617	5.67%	1.04%	5.59%	6.75%
Tuscarawas	556	6.25%	1.32%	5.44%	7.64%
Union	286	3.07%	0.85%	4.41%	7.26%
Van Wert	301	7.05%	2.88%	5.53%	7.02%
Vinton	235	7.30%	1.97%	5.07%	8.87%
Warren	748	4.17%	0.89%	4.45%	5.66%

Continued on next page

Table 6 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	6.81%	1.47%	5.45%	8.19%
Wayne	661	8.84%	1.59%	4.99%	7.93%
Williams	337	5.21%	1.63%	5.29%	6.88%
Wood	687	5.34%	1.04%	4.35%	8.21%
Wyandot	288	6.94%	1.82%	5.51%	7.87%
Total	50944				

Table 7: Comparing Coronary Heart Disease Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	5.06%	1.39%	6.16%	10.33%
Allen	394	8.15%	1.65%	6.09%	9.80%
Ashland	323	5.37%	1.32%	6.16%	8.97%
Ashtabula	403	6.89%	1.41%	6.38%	9.04%
Athens	336	9.70%	2.12%	4.11%	9.73%
Auglaize	272	7.62%	1.74%	6.24%	9.80%
Belmont	348	9.02%	1.65%	6.91%	8.90%
Brown	662	7.78%	1.26%	5.71%	10.33%
Butler	1284	6.33%	0.75%	5.20%	8.20%
Carroll	303	7.44%	3.18%	6.48%	8.80%
Champaign	314	10.71%	3.14%	6.02%	8.80%
Clark	407	7.14%	1.43%	6.34%	8.80%
Clermont	1060	6.51%	0.88%	5.14%	8.96%
Clinton	293	7.13%	2.35%	5.63%	8.96%
Columbiana	466	4.79%	1.03%	6.39%	8.45%
Coshocton	376	5.93%	1.43%	6.48%	9.38%
Crawford	291	9.00%	2.00%	6.51%	8.99%
Cuyahoga	4103	5.63%	0.42%	6.29%	7.74%
Darke	469	7.65%	1.92%	6.53%	8.73%
Defiance	337	3.59%	1.03%	6.00%	8.90%
Delaware	335	3.82%	1.11%	4.91%	7.43%
Erie	407	6.82%	1.36%	6.70%	8.78%
Fairfield	288	6.86%	1.73%	5.64%	8.15%
Fayette	279	7.10%	1.62%	6.28%	8.80%
Franklin	3118	5.39%	0.48%	4.74%	6.75%
Fulton	266	6.22%	1.63%	5.97%	8.81%
Gallia	310	5.74%	1.79%	6.11%	9.73%
Geauga	262	6.21%	1.60%	6.23%	8.45%
Greene	350	6.79%	1.37%	5.51%	8.80%
Guernsey	290	5.49%	1.29%	6.41%	9.61%
Hamilton	2266	5.81%	0.57%	5.78%	7.20%
Hancock	396	5.28%	1.13%	5.87%	8.81%
Hardin	280	10.86%	3.16%	5.60%	9.20%
Harrison	262	6.81%	1.72%	7.11%	8.90%
Henry	303	5.67%	1.50%	6.19%	8.81%
Highland	634	8.36%	1.66%	6.23%	10.24%
Hocking	269	6.32%	1.86%	6.25%	9.24%
Holmes	326	6.20%	1.43%	5.48%	9.38%
Huron	402	5.20%	1.14%	5.83%	8.97%
Jackson	307	14.54%	3.92%	6.02%	10.33%
Jefferson	338	5.05%	1.00%	7.07%	8.90%

Continued on next page

Table 7 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	7.43%	1.51%	6.00%	9.28%
Lake	377	5.54%	1.30%	6.20%	7.74%
Lawrence	359	8.07%	1.66%	6.31%	9.73%
Licking	286	6.63%	1.54%	5.78%	8.31%
Logan	296	7.29%	1.66%	6.23%	9.20%
Lorain	1878	7.70%	0.88%	5.84%	8.78%
Lucas	1857	6.11%	0.70%	5.75%	8.81%
Madison	280	6.16%	1.76%	5.39%	8.78%
Mahoning	1324	6.17%	0.84%	6.83%	8.07%
Marion	398	12.35%	2.30%	5.94%	8.87%
Medina	251	4.84%	1.45%	5.58%	7.74%
Meigs	480	8.22%	2.06%	6.40%	9.73%
Mercer	329	5.41%	1.51%	6.38%	8.73%
Miami	332	7.50%	1.79%	6.14%	8.80%
Monroe	232	3.31%	1.12%	7.00%	9.05%
Montgomery	1770	6.60%	0.71%	5.94%	8.80%
Morgan	319	3.45%	0.96%	6.71%	9.68%
Morrow	266	5.91%	1.79%	5.84%	8.41%
Muskingum	337	10.62%	2.22%	6.17%	9.61%
Noble	261	10.03%	2.31%	5.60%	9.73%
Ottawa	316	5.95%	1.47%	6.95%	8.81%
Paulding	320	9.93%	3.51%	5.97%	8.90%
Perry	267	5.11%	1.54%	5.81%	8.68%
Pickaway	282	4.46%	1.11%	5.44%	7.64%
Pike	406	5.93%	1.43%	6.05%	9.24%
Portage	285	8.17%	1.83%	5.23%	8.60%
Preble	354	9.40%	2.56%	6.14%	8.73%
Putnam	306	7.45%	1.89%	6.03%	8.90%
Richland	341	7.28%	1.58%	6.24%	8.99%
Ross	365	4.58%	1.46%	5.71%	7.64%
Sandusky	398	6.84%	1.40%	6.28%	8.81%
Scioto	462	7.66%	1.67%	6.22%	10.33%
Seneca	361	4.45%	1.57%	6.06%	8.81%
Shelby	326	5.65%	1.42%	5.80%	9.20%
Stark	1137	7.16%	0.86%	6.37%	8.90%
Summit	3346	5.51%	0.56%	6.06%	8.04%
Trumbull	617	8.47%	1.37%	6.58%	8.64%
Tuscarawas	556	6.68%	1.40%	6.38%	8.90%
Union	286	3.84%	0.93%	5.07%	8.87%
Van Wert	301	6.66%	1.84%	6.48%	8.90%
Vinton	235	8.68%	1.99%	5.92%	9.73%
Warren	748	4.71%	0.87%	5.10%	8.20%

Continued on next page

Table 7 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	7.06%	1.38%	6.40%	9.73%
Wayne	661	8.30%	1.40%	5.81%	8.84%
Williams	337	5.92%	1.26%	6.18%	8.33%
Wood	687	4.95%	0.82%	5.02%	8.81%
Wyandot	288	8.88%	2.36%	6.46%	8.87%
Total	50944				

Table 8: Comparing Stroke Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	7.15%	3.32%	3.38%	5.34%
Allen	394	2.92%	0.81%	3.37%	4.61%
Ashland	323	2.68%	0.98%	3.39%	4.67%
Ashtabula	403	2.82%	0.78%	3.51%	4.66%
Athens	336	6.08%	1.82%	2.32%	4.86%
Auglaize	272	4.85%	1.53%	3.46%	4.61%
Belmont	348	4.28%	1.30%	3.80%	5.03%
Brown	662	5.50%	1.09%	3.18%	5.34%
Butler	1284	2.72%	0.51%	2.93%	4.53%
Carroll	303	2.31%	0.96%	3.53%	4.51%
Champaign	314	5.40%	2.17%	3.33%	4.58%
Clark	407	5.95%	1.36%	3.49%	4.61%
Clermont	1060	3.71%	0.83%	2.92%	4.53%
Clinton	293	5.49%	2.42%	3.15%	4.68%
Columbiana	466	4.90%	1.36%	3.52%	4.66%
Coshocton	376	6.11%	1.71%	3.55%	4.67%
Crawford	291	4.46%	1.17%	3.57%	4.86%
Cuyahoga	4103	3.51%	0.34%	3.50%	4.67%
Darke	469	3.62%	1.38%	3.58%	4.75%
Defiance	337	2.53%	0.91%	3.32%	4.28%
Delaware	335	1.30%	0.71%	2.80%	3.92%
Erie	407	2.01%	0.68%	3.65%	4.67%
Fairfield	288	6.29%	1.65%	3.15%	4.70%
Fayette	279	3.80%	1.34%	3.46%	4.97%
Franklin	3118	3.00%	0.36%	2.73%	3.92%
Fulton	266	2.31%	1.31%	3.32%	4.08%
Gallia	310	4.63%	1.78%	3.37%	4.91%
Geauga	262	2.19%	1.34%	3.43%	4.67%
Greene	350	4.06%	1.29%	3.06%	4.53%
Guernsey	290	3.47%	0.95%	3.52%	4.95%
Hamilton	2266	3.53%	0.44%	3.25%	4.53%
Hancock	396	2.89%	0.72%	3.27%	4.61%
Hardin	280	4.10%	1.49%	3.10%	4.61%
Harrison	262	3.34%	1.11%	3.86%	4.95%
Henry	303	2.88%	0.93%	3.43%	4.52%
Highland	634	4.95%	1.50%	3.42%	4.68%
Hocking	269	2.39%	0.98%	3.40%	4.27%
Holmes	326	3.31%	0.94%	3.05%	4.67%
Huron	402	3.97%	1.02%	3.25%	4.86%
Jackson	307	7.46%	2.81%	3.35%	5.20%
Jefferson	338	2.69%	1.08%	3.86%	4.51%

Continued on next page

Table 8 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	6.63%	2.03%	3.32%	4.70%
Lake	377	2.27%	0.83%	3.44%	4.66%
Lawrence	359	4.34%	1.19%	3.47%	5.50%
Licking	286	1.75%	0.71%	3.21%	4.00%
Logan	296	3.05%	0.86%	3.44%	4.61%
Lorain	1878	3.62%	0.62%	3.25%	4.67%
Lucas	1857	3.37%	0.51%	3.23%	5.65%
Madison	280	4.29%	1.76%	3.01%	4.13%
Mahoning	1324	3.88%	0.75%	3.75%	4.51%
Marion	398	3.14%	0.82%	3.30%	4.37%
Medina	251	1.96%	0.85%	3.12%	4.67%
Meigs	480	3.54%	1.53%	3.51%	4.91%
Mercer	329	1.97%	0.76%	3.51%	4.75%
Miami	332	4.86%	1.45%	3.40%	5.01%
Monroe	232	5.60%	2.17%	3.77%	5.03%
Montgomery	1770	4.16%	0.56%	3.31%	5.22%
Morgan	319	2.15%	0.68%	3.65%	4.99%
Morrow	266	2.31%	1.28%	3.23%	4.00%
Muskingum	337	4.27%	1.27%	3.42%	4.67%
Noble	261	5.87%	1.66%	3.11%	5.03%
Ottawa	316	2.83%	1.11%	3.77%	4.67%
Paulding	320	5.21%	1.42%	3.30%	4.28%
Perry	267	3.19%	1.19%	3.22%	4.70%
Pickaway	282	3.90%	1.79%	3.02%	4.21%
Pike	406	4.13%	1.20%	3.34%	5.14%
Portage	285	3.97%	1.27%	2.92%	4.67%
Preble	354	6.33%	2.31%	3.39%	4.53%
Putnam	306	3.28%	1.21%	3.35%	4.41%
Richland	341	4.47%	1.27%	3.44%	4.86%
Ross	365	3.60%	1.29%	3.17%	5.25%
Sandusky	398	4.18%	1.18%	3.47%	5.08%
Scioto	462	3.88%	0.91%	3.44%	5.34%
Seneca	361	2.02%	0.65%	3.36%	4.88%
Shelby	326	2.43%	0.90%	3.23%	4.61%
Stark	1137	2.61%	0.52%	3.52%	4.10%
Summit	3346	3.04%	0.38%	3.37%	4.67%
Trumbull	617	4.65%	1.04%	3.61%	4.66%
Tuscarawas	556	3.22%	0.91%	3.52%	4.49%
Union	286	3.06%	1.26%	2.89%	4.40%
Van Wert	301	2.02%	0.94%	3.57%	4.28%
Vinton	235	3.73%	1.40%	3.26%	4.99%
Warren	748	2.45%	0.85%	2.90%	4.53%

Continued on next page

Table 8 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	2.53%	0.72%	3.52%	5.03%
Wayne	661	2.60%	0.67%	3.23%	4.67%
Williams	337	1.69%	0.72%	3.41%	4.03%
Wood	687	2.04%	0.46%	2.82%	4.52%
Wyandot	288	2.59%	1.18%	3.56%	4.37%

Table 9: Comparing Congestive Heart Failure Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	3.55%	1.34%	2.93%	5.02%
Allen	394	2.80%	0.95%	2.93%	4.39%
Ashland	323	3.11%	1.14%	2.95%	4.06%
Ashtabula	403	2.44%	0.73%	3.05%	4.24%
Athens	336	2.13%	0.82%	2.03%	4.35%
Auglaize	272	4.49%	1.43%	3.00%	4.44%
Belmont	348	4.45%	1.16%	3.31%	4.21%
Brown	662	3.76%	0.78%	2.74%	5.02%
Butler	1284	2.31%	0.49%	2.53%	3.38%
Carroll	303	2.12%	0.61%	3.07%	4.21%
Champaign	314	5.38%	2.24%	2.88%	4.44%
Clark	407	2.19%	0.82%	3.04%	4.33%
Clermont	1060	3.15%	0.63%	2.50%	4.07%
Clinton	293	5.70%	2.46%	2.72%	4.56%
Columbiana	466	2.37%	0.71%	3.05%	4.08%
Coshocton	376	2.71%	0.75%	3.09%	4.35%
Crawford	291	2.96%	0.95%	3.10%	4.55%
Cuyahoga	4103	2.76%	0.29%	3.03%	4.05%
Darke	469	4.25%	1.65%	3.11%	4.07%
Defiance	337	1.25%	0.66%	2.88%	3.79%
Delaware	335	1.51%	0.74%	2.39%	4.10%
Erie	407	1.34%	0.59%	3.18%	4.05%
Fairfield	288	5.84%	1.66%	2.71%	4.10%
Fayette	279	4.52%	1.33%	3.00%	4.33%
Franklin	3118	3.27%	0.37%	2.33%	4.10%
Fulton	266	2.40%	0.80%	2.87%	4.50%
Gallia	310	2.43%	0.75%	2.92%	4.35%
Geauga	262	1.45%	0.65%	2.97%	4.05%
Greene	350	1.84%	0.74%	2.65%	4.07%
Guernsey	290	2.37%	0.79%	3.05%	4.35%
Hamilton	2266	2.61%	0.39%	2.80%	3.38%
Hancock	396	3.17%	0.91%	2.83%	4.38%
Hardin	280	4.26%	1.47%	2.70%	4.38%
Harrison	262	3.46%	1.33%	3.37%	4.21%
Henry	303	2.39%	1.05%	2.97%	4.50%
Highland	634	3.78%	0.91%	2.97%	4.77%
Hocking	269	1.77%	0.63%	2.96%	4.20%
Holmes	326	2.35%	0.79%	2.64%	4.16%
Huron	402	1.72%	0.56%	2.81%	4.05%
Jackson	307	10.59%	4.00%	2.90%	5.02%
Jefferson	338	2.66%	0.82%	3.37%	4.21%

Continued on next page

Table 9 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	4.83%	1.99%	2.88%	4.16%
Lake	377	2.17%	0.84%	2.97%	4.05%
Lawrence	359	4.62%	1.30%	3.01%	5.02%
Licking	286	2.02%	0.92%	2.77%	4.10%
Logan	296	5.81%	1.50%	2.98%	4.39%
Lorain	1878	2.77%	0.53%	2.81%	4.05%
Lucas	1857	2.42%	0.39%	2.79%	4.50%
Madison	280	3.00%	1.14%	2.60%	4.10%
Mahoning	1324	3.09%	0.62%	3.27%	4.08%
Marion	398	6.51%	1.85%	2.86%	4.55%
Medina	251	0.98%	0.54%	2.69%	4.05%
Meigs	480	3.75%	1.34%	3.05%	5.02%
Mercer	329	2.56%	1.00%	3.05%	4.07%
Miami	332	4.71%	1.47%	2.94%	4.44%
Monroe	232	10.50%	5.02%	3.29%	4.21%
Montgomery	1770	3.13%	0.51%	2.86%	4.33%
Morgan	319	2.46%	1.15%	3.18%	4.35%
Morrow	266	3.03%	1.24%	2.79%	4.22%
Muskingum	337	5.81%	1.74%	2.96%	4.35%
Noble	261	3.95%	1.49%	2.70%	4.35%
Ottawa	316	1.82%	0.70%	3.29%	4.05%
Paulding	320	9.09%	3.70%	2.86%	4.04%
Perry	267	0.62%	0.28%	2.79%	4.10%
Pickaway	282	2.74%	0.86%	2.61%	4.20%
Pike	406	1.98%	0.57%	2.89%	4.77%
Portage	285	4.77%	1.43%	2.53%	4.12%
Preble	354	3.25%	1.16%	2.93%	4.07%
Putnam	306	3.02%	1.17%	2.91%	4.39%
Richland	341	3.72%	1.09%	2.98%	4.55%
Ross	365	4.58%	1.84%	2.74%	4.20%
Sandusky	398	1.67%	0.56%	3.01%	4.38%
Scioto	462	3.33%	0.69%	2.98%	5.02%
Seneca	361	2.07%	0.62%	2.92%	4.55%
Shelby	326	4.99%	1.86%	2.79%	4.44%
Stark	1137	2.45%	0.46%	3.06%	4.00%
Summit	3346	3.04%	0.44%	2.92%	4.05%
Trumbull	617	5.42%	1.15%	3.14%	4.21%
Tuscarawas	556	1.57%	0.49%	3.05%	4.00%
Union	286	1.54%	0.65%	2.47%	4.10%
Van Wert	301	1.43%	0.96%	3.10%	3.79%
Vinton	235	3.40%	1.28%	2.82%	4.71%
Warren	748	2.99%	0.76%	2.48%	3.68%

Continued on next page

Table 9 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	2.79%	0.82%	3.05%	4.35%
Wayne	661	4.00%	1.06%	2.79%	4.16%
Williams	337	2.30%	0.83%	2.96%	3.49%
Wood	687	1.55%	0.42%	2.45%	4.38%
Wyandot	288	4.60%	1.61%	3.09%	4.27%
Total	50944				

Table 10: Comparing Diabetes Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	18.16%	4.09%	11.17%	16.07%
Allen	394	10.55%	1.79%	11.01%	14.94%
Ashland	323	10.76%	2.26%	11.12%	14.13%
Ashtabula	403	10.78%	1.84%	11.48%	13.49%
Athens	336	9.69%	2.04%	8.16%	15.02%
Auglaize	272	12.23%	2.24%	11.29%	14.94%
Belmont	348	13.43%	2.22%	12.06%	15.75%
Brown	662	11.46%	1.77%	10.69%	14.74%
Butler	1284	10.79%	1.00%	10.02%	13.54%
Carroll	303	10.35%	2.86%	11.60%	14.51%
Champaign	314	11.00%	2.48%	11.10%	15.28%
Clark	407	13.91%	2.02%	11.43%	15.28%
Clermont	1060	12.81%	1.34%	10.09%	14.05%
Clinton	293	18.23%	3.11%	10.54%	17.60%
Columbiana	466	13.13%	1.86%	11.45%	15.75%
Coshocton	376	12.30%	2.05%	11.58%	15.02%
Crawford	291	8.95%	1.67%	11.62%	14.84%
Cuyahoga	4103	10.41%	0.57%	11.40%	14.02%
Darke	469	8.76%	1.70%	11.61%	13.56%
Defiance	337	11.45%	3.29%	11.00%	13.56%
Delaware	335	7.59%	1.62%	9.87%	14.36%
Erie	407	12.39%	2.26%	11.86%	14.02%
Fairfield	288	13.71%	2.38%	10.63%	14.44%
Fayette	279	15.32%	2.62%	11.33%	16.07%
Franklin	3118	11.46%	0.68%	9.48%	14.36%
Fulton	266	10.00%	2.12%	11.01%	16.29%
Gallia	310	13.68%	3.39%	11.15%	15.81%
Geauga	262	8.56%	2.05%	11.43%	14.02%
Greene	350	12.42%	2.01%	10.32%	15.28%
Guernsey	290	9.99%	1.89%	11.51%	15.35%
Hamilton	2266	10.59%	0.75%	10.77%	13.54%
Hancock	396	11.95%	2.01%	10.83%	15.31%
Hardin	280	17.36%	3.55%	10.31%	14.94%
Harrison	262	10.14%	2.19%	12.33%	15.23%
Henry	303	7.60%	1.59%	11.24%	16.29%
Highland	634	12.29%	2.21%	11.25%	16.00%
Hocking	269	14.68%	3.82%	11.26%	14.96%
Holmes	326	8.51%	1.78%	10.24%	14.22%
Huron	402	16.10%	2.87%	10.82%	14.84%
Jackson	307	21.77%	4.30%	11.06%	16.07%
Jefferson	338	11.08%	1.73%	12.27%	15.75%

Continued on next page

Table 10 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	15.72%	3.12%	10.93%	14.96%
Lake	377	11.74%	1.79%	11.32%	14.02%
Lawrence	359	14.01%	2.17%	11.42%	17.81%
Licking	286	12.39%	2.11%	10.80%	14.96%
Logan	296	10.25%	1.78%	11.28%	15.28%
Lorain	1878	10.33%	0.90%	10.84%	14.02%
Lucas	1857	10.73%	0.92%	10.71%	16.29%
Madison	280	16.57%	3.27%	10.14%	14.36%
Mahoning	1324	12.27%	1.27%	11.96%	14.16%
Marion	398	16.14%	2.76%	10.87%	14.36%
Medina	251	8.61%	1.87%	10.63%	14.02%
Meigs	480	13.40%	3.05%	11.49%	16.97%
Mercer	329	8.30%	1.78%	11.39%	13.56%
Miami	332	15.28%	2.40%	11.24%	15.28%
Monroe	232	8.44%	2.09%	12.17%	15.69%
Montgomery	1770	14.24%	1.03%	10.94%	17.60%
Morgan	319	9.90%	2.17%	11.83%	15.35%
Morrow	266	9.51%	1.93%	10.86%	14.84%
Muskingum	337	11.49%	1.98%	11.20%	15.02%
Noble	261	14.37%	3.10%	10.14%	15.35%
Ottawa	316	9.29%	1.90%	12.17%	14.02%
Paulding	320	17.02%	3.33%	10.99%	13.56%
Perry	267	11.00%	2.27%	10.77%	15.02%
Pickaway	282	10.15%	2.21%	10.17%	14.58%
Pike	406	15.57%	2.51%	11.03%	16.07%
Portage	285	12.12%	2.04%	9.96%	14.02%
Preble	354	10.82%	1.94%	11.21%	13.54%
Putnam	306	8.72%	1.92%	11.00%	14.94%
Richland	341	12.25%	1.94%	11.25%	14.84%
Ross	365	13.13%	2.35%	10.59%	16.07%
Sandusky	398	10.22%	1.78%	11.35%	14.45%
Scioto	462	11.69%	1.81%	11.22%	16.07%
Seneca	361	11.69%	2.07%	10.98%	16.10%
Shelby	326	10.61%	2.03%	10.77%	14.94%
Stark	1137	10.00%	1.00%	11.48%	13.33%
Summit	3346	10.68%	0.75%	11.11%	14.02%
Trumbull	617	12.70%	1.69%	11.71%	14.02%
Tuscarawas	556	10.71%	1.53%	11.47%	14.92%
Union	286	8.53%	2.07%	10.06%	14.48%
Van Wert	301	9.43%	2.48%	11.55%	13.56%
Vinton	235	19.78%	6.35%	10.89%	16.07%
Warren	748	8.94%	1.32%	10.00%	13.54%

Continued on next page

Table 10 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	11.57%	2.04%	11.50%	15.02%
Wayne	661	12.02%	1.60%	10.76%	14.35%
Williams	337	8.49%	1.78%	11.20%	12.99%
Wood	687	11.77%	1.67%	9.63%	16.29%
Wyandot	288	9.30%	2.13%	11.52%	14.45%
Total	50944				

Table 11: Comparing Cancer Estimates

County	N	Survey-Weighted Estimate	SE	Synthetic Estimate	Smoothed Estimate
Adams	490	6.04%	1.13%	9.31%	13.40%
Allen	394	8.22%	1.34%	9.25%	12.93%
Ashland	323	8.21%	1.45%	9.34%	13.14%
Ashtabula	403	11.44%	1.94%	9.67%	13.08%
Athens	336	8.59%	1.52%	6.60%	13.38%
Auglaize	272	10.51%	2.09%	9.52%	12.93%
Belmont	348	11.05%	2.01%	10.36%	12.98%
Brown	662	8.42%	1.14%	8.78%	13.40%
Butler	1284	10.08%	0.92%	8.18%	13.55%
Carroll	303	6.96%	1.78%	9.69%	12.64%
Champaign	314	8.93%	1.92%	9.17%	12.96%
Clark	407	7.24%	1.31%	9.64%	12.84%
Clermont	1060	9.94%	1.01%	8.12%	13.55%
Clinton	293	8.53%	1.95%	8.72%	12.84%
Columbiana	466	11.09%	1.89%	9.63%	12.92%
Coshocton	376	12.40%	2.35%	9.76%	13.25%
Crawford	291	12.51%	2.86%	9.83%	13.03%
Cuyahoga	4103	8.33%	0.51%	9.71%	11.08%
Darke	469	9.76%	1.58%	9.82%	13.34%
Defiance	337	7.89%	1.61%	9.13%	12.82%
Delaware	335	10.86%	1.88%	7.81%	12.84%
Erie	407	9.25%	1.56%	10.02%	12.76%
Fairfield	288	12.76%	2.16%	8.70%	13.13%
Fayette	279	9.31%	2.06%	9.52%	12.96%
Franklin	3118	8.64%	0.58%	7.69%	11.88%
Fulton	266	9.44%	1.98%	9.15%	12.51%
Gallia	310	10.82%	2.05%	9.29%	13.63%
Geauga	262	10.44%	2.05%	9.41%	12.80%
Greene	350	12.81%	1.92%	8.51%	13.09%
Guernsey	290	9.14%	2.20%	9.68%	13.25%
Hamilton	2266	10.70%	0.73%	9.04%	13.55%
Hancock	396	5.78%	0.99%	9.03%	12.78%
Hardin	280	9.27%	2.04%	8.62%	12.96%
Harrison	262	11.54%	4.33%	10.55%	12.98%
Henry	303	9.01%	1.83%	9.44%	12.82%
Highland	634	6.29%	1.04%	9.44%	12.83%
Hocking	269	13.63%	3.32%	9.32%	13.13%
Holmes	326	7.18%	1.37%	8.47%	13.25%
Huron	402	8.93%	1.68%	8.99%	13.06%
Jackson	307	15.11%	3.77%	9.26%	13.38%
Jefferson	338	9.08%	1.93%	10.58%	12.64%

Continued on next page

Table 11 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	9.68%	1.69%	9.15%	13.14%
Lake	377	11.33%	1.71%	9.48%	12.82%
Lawrence	359	13.57%	2.45%	9.60%	14.14%
Licking	286	11.44%	1.98%	8.90%	13.14%
Logan	296	8.94%	1.95%	9.45%	12.84%
Lorain	1878	9.59%	1.01%	8.99%	12.51%
Lucas	1857	7.61%	0.72%	8.96%	11.52%
Madison	280	8.75%	1.91%	8.16%	12.96%
Mahoning	1324	8.71%	0.93%	10.31%	12.64%
Marion	398	9.05%	1.87%	9.00%	12.97%
Medina	251	11.69%	2.15%	8.64%	12.76%
Meigs	480	7.79%	1.94%	9.65%	13.34%
Mercer	329	5.68%	1.27%	9.62%	12.82%
Miami	332	13.68%	2.11%	9.36%	12.83%
Monroe	232	20.77%	7.22%	10.31%	12.93%
Montgomery	1770	10.37%	0.86%	9.18%	12.83%
Morgan	319	4.13%	1.09%	9.98%	13.25%
Morrow	266	11.81%	3.04%	8.88%	12.84%
Muskingum	337	9.22%	1.65%	9.44%	13.25%
Noble	261	6.61%	1.47%	8.34%	12.98%
Ottawa	316	12.09%	2.64%	10.31%	12.51%
Paulding	320	11.52%	3.55%	9.08%	12.82%
Perry	267	9.14%	2.03%	8.88%	13.14%
Pickaway	282	7.65%	1.66%	8.17%	12.55%
Pike	406	5.57%	1.01%	9.23%	13.09%
Portage	285	12.99%	2.14%	8.15%	12.82%
Preble	354	13.51%	2.63%	9.31%	13.55%
Putnam	306	5.60%	1.42%	9.21%	12.93%
Richland	341	11.22%	1.96%	9.41%	13.14%
Ross	365	7.65%	1.56%	8.65%	12.79%
Sandusky	398	8.50%	1.56%	9.55%	12.97%
Scioto	462	10.89%	1.91%	9.49%	13.40%
Seneca	361	9.84%	2.02%	9.24%	12.97%
Shelby	326	6.45%	1.30%	8.92%	12.83%
Stark	1137	9.90%	0.99%	9.72%	12.76%
Summit	3346	8.69%	0.67%	9.33%	12.49%
Trumbull	617	9.69%	1.29%	9.93%	12.92%
Tuscarawas	556	7.61%	1.34%	9.69%	12.76%
Union	286	6.88%	1.54%	8.14%	12.86%
Van Wert	301	7.15%	1.83%	9.80%	12.82%
Vinton	235	9.79%	2.87%	8.99%	13.38%
Warren	748	9.74%	1.26%	8.02%	12.83%

Continued on next page

Table 11 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	9.21%	1.49%	9.68%	13.34%
Wayne	661	6.40%	0.95%	8.91%	12.51%
Williams	337	5.77%	1.31%	9.36%	12.76%
Wood	687	8.69%	1.27%	7.89%	12.51%
Wyandot	288	8.25%	1.73%	9.77%	12.78%

Table 12: Comparing Obesity Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	30.58%	4.92%	29.11%	31.57%
Allen	394	26.72%	2.95%	28.86%	30.93%
Ashland	323	35.56%	4.06%	28.81%	30.04%
Ashtabula	403	27.69%	2.87%	29.26%	30.76%
Athens	336	26.41%	3.56%	25.81%	32.21%
Auglaize	272	33.43%	4.17%	29.16%	32.01%
Belmont	348	30.71%	3.33%	29.35%	31.88%
Brown	662	36.83%	3.82%	29.14%	31.57%
Butler	1284	26.62%	1.60%	28.52%	28.48%
Carroll	303	27.75%	4.53%	29.49%	30.39%
Champaign	314	37.01%	4.38%	29.29%	32.01%
Clark	407	37.58%	3.07%	29.08%	32.01%
Clermont	1060	31.73%	2.08%	29.10%	31.29%
Clinton	293	31.55%	4.47%	28.81%	31.68%
Columbiana	466	32.35%	3.04%	29.29%	31.99%
Coshocton	376	32.23%	4.01%	29.29%	32.09%
Crawford	291	31.25%	4.04%	29.23%	32.92%
Cuyahoga	4103	25.59%	0.89%	29.10%	29.24%
Darke	469	27.95%	3.50%	29.24%	30.59%
Defiance	337	31.57%	3.73%	29.07%	30.93%
Delaware	335	22.15%	2.69%	29.29%	30.74%
Erie	407	30.47%	3.27%	29.46%	30.04%
Fairfield	288	36.91%	3.41%	29.22%	32.37%
Fayette	279	22.92%	3.41%	29.19%	30.74%
Franklin	3118	30.15%	1.07%	28.33%	30.74%
Fulton	266	31.58%	3.97%	29.19%	32.02%
Gallia	310	27.89%	3.72%	29.02%	32.21%
Geauga	262	25.79%	3.39%	29.72%	29.24%
Greene	350	27.40%	2.80%	28.41%	30.83%
Guernsey	290	28.25%	4.19%	29.26%	32.03%
Hamilton	2266	27.61%	1.20%	28.81%	28.48%
Hancock	396	27.43%	3.22%	28.86%	30.96%
Hardin	280	34.48%	4.64%	27.96%	32.01%
Harrison	262	31.20%	4.71%	29.52%	31.88%
Henry	303	31.85%	4.82%	29.16%	31.31%
Highland	634	31.40%	4.18%	29.09%	30.83%
Hocking	269	33.73%	5.15%	29.29%	33.11%
Holmes	326	26.59%	4.36%	28.38%	32.09%
Huron	402	31.44%	3.55%	29.00%	32.42%
Jackson	307	37.99%	4.82%	29.03%	32.88%
Jefferson	338	29.77%	3.24%	29.28%	31.99%

Continued on next page

Table 12 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	32.16%	3.88%	28.66%	31.20%
Lake	377	26.16%	2.53%	29.40%	29.24%
Lawrence	359	34.16%	3.68%	29.15%	33.80%
Licking	286	31.55%	3.12%	29.16%	31.20%
Logan	296	30.01%	3.74%	29.17%	32.01%
Lorain	1878	30.18%	1.70%	29.11%	30.04%
Lucas	1857	30.95%	1.54%	28.78%	35.61%
Madison	280	36.93%	4.68%	29.04%	30.74%
Mahoning	1324	29.57%	1.89%	29.15%	29.38%
Marion	398	33.04%	3.56%	29.18%	30.74%
Medina	251	24.94%	2.98%	29.44%	29.24%
Meigs	480	21.92%	3.70%	29.23%	32.40%
Mercer	329	24.89%	3.55%	29.13%	31.26%
Miami	332	30.49%	3.13%	29.35%	32.01%
Monroe	232	30.04%	6.21%	29.56%	32.21%
Montgomery	1770	29.76%	1.47%	28.89%	32.01%
Morgan	319	46.60%	7.65%	29.35%	32.21%
Morrow	266	35.17%	4.69%	29.34%	31.20%
Muskingum	337	36.61%	3.52%	28.94%	32.21%
Noble	261	37.30%	6.28%	28.53%	32.21%
Ottawa	316	37.38%	4.15%	29.68%	31.54%
Paulding	320	38.09%	5.89%	29.14%	31.26%
Perry	267	31.11%	4.12%	29.06%	31.20%
Pickaway	282	34.99%	4.27%	29.09%	33.11%
Pike	406	30.91%	4.85%	28.96%	32.88%
Portage	285	29.65%	3.07%	28.23%	29.71%
Preble	354	33.99%	3.91%	29.32%	31.26%
Putnam	306	35.13%	4.71%	29.03%	31.54%
Richland	341	28.94%	3.08%	29.22%	31.20%
Ross	365	35.88%	3.67%	29.16%	33.11%
Sandusky	398	35.74%	3.72%	29.17%	33.12%
Scioto	462	34.06%	3.40%	28.89%	32.69%
Seneca	361	26.16%	3.39%	28.77%	32.92%
Shelby	326	31.36%	4.01%	29.08%	32.01%
Stark	1137	25.83%	1.61%	29.19%	28.52%
Summit	3346	27.23%	1.26%	29.12%	29.24%
Trumbull	617	32.55%	2.35%	29.31%	30.76%
Tuscarawas	556	28.93%	2.92%	29.24%	29.99%
Union	286	24.75%	3.88%	29.08%	30.74%
Van Wert	301	26.72%	4.91%	29.11%	30.93%
Vinton	235	29.05%	5.17%	29.07%	33.11%
Warren	748	26.38%	2.18%	29.27%	28.48%

Continued on next page

Table 12 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	32.94%	3.52%	29.21%	32.21%
Wayne	661	22.34%	2.22%	28.91%	29.24%
Williams	337	29.04%	3.98%	29.17%	30.93%
Wood	687	28.77%	2.42%	27.75%	31.54%
Wyandot	288	30.08%	4.83%	29.12%	30.96%
Total	50944				

Table 13: Comparing Need Rx Estimates

County	N	Survey-Weighted Estimate	SE	Synthetic Estimate	Smoothed Estimate
Adams	490	21.43%	4.71%	15.26%	16.66%
Allen	394	14.85%	2.51%	15.08%	13.38%
Ashland	323	14.37%	3.03%	15.17%	13.45%
Ashtabula	403	12.88%	2.09%	15.18%	13.55%
Athens	336	15.44%	3.11%	15.49%	14.41%
Auglaize	272	13.91%	2.96%	15.18%	13.38%
Belmont	348	14.81%	2.68%	14.72%	13.76%
Brown	662	22.73%	3.19%	15.57%	16.93%
Butler	1284	14.42%	1.26%	15.72%	13.20%
Carroll	303	15.63%	4.18%	15.18%	13.60%
Champaign	314	14.12%	3.13%	15.41%	13.51%
Clark	407	20.57%	2.52%	15.17%	13.28%
Clermont	1060	18.09%	1.69%	15.94%	16.93%
Clinton	293	23.99%	4.27%	15.49%	15.66%
Columbiana	466	17.40%	2.43%	15.07%	13.55%
Coshocton	376	12.42%	2.24%	15.09%	13.45%
Crawford	291	13.90%	3.10%	15.07%	13.30%
Cuyahoga	4103	13.90%	0.71%	15.26%	14.09%
Darke	469	11.82%	2.26%	15.02%	12.95%
Defiance	337	12.12%	2.59%	15.30%	12.44%
Delaware	335	16.23%	2.43%	16.17%	13.86%
Erie	407	10.97%	2.05%	15.08%	13.30%
Fairfield	288	14.28%	2.49%	15.59%	16.89%
Fayette	279	8.95%	2.08%	15.22%	14.84%
Franklin	3118	18.20%	0.89%	15.96%	16.89%
Fulton	266	10.05%	2.58%	15.38%	13.03%
Gallia	310	21.81%	4.12%	15.29%	15.60%
Geauga	262	12.25%	2.46%	15.41%	13.59%
Greene	350	11.82%	2.04%	15.49%	13.28%
Guernsey	290	23.70%	4.63%	15.18%	14.19%
Hamilton	2266	13.18%	0.90%	15.46%	13.20%
Hancock	396	14.25%	2.64%	15.38%	13.34%
Hardin	280	13.81%	2.65%	15.21%	13.51%
Harrison	262	22.76%	5.49%	14.81%	14.38%
Henry	303	11.00%	3.11%	15.22%	13.03%
Highland	634	18.54%	3.27%	15.23%	16.21%
Hocking	269	20.84%	4.79%	15.25%	16.81%
Holmes	326	12.21%	3.88%	15.44%	13.45%
Huron	402	19.05%	3.44%	15.44%	13.50%
Jackson	307	18.73%	3.68%	15.34%	16.66%
Jefferson	338	13.90%	2.80%	14.76%	13.55%

Continued on next page

Table 13 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	15.31%	3.14%	15.22%	13.45%
Lake	377	13.29%	1.90%	15.33%	14.09%
Lawrence	359	22.36%	3.41%	15.25%	15.60%
Licking	286	12.97%	2.23%	15.55%	13.86%
Logan	296	12.19%	3.20%	15.23%	13.34%
Lorain	1878	13.50%	1.32%	15.46%	14.09%
Lucas	1857	18.37%	1.33%	15.46%	17.86%
Madison	280	17.26%	3.43%	15.28%	16.89%
Mahoning	1324	15.71%	1.52%	14.84%	13.55%
Marion	398	15.30%	2.87%	15.17%	14.10%
Medina	251	11.67%	2.18%	15.75%	13.57%
Meigs	480	17.94%	3.76%	15.13%	15.60%
Mercer	329	7.24%	2.32%	15.07%	12.63%
Miami	332	15.21%	2.74%	15.35%	13.22%
Monroe	232	19.43%	7.16%	14.86%	14.19%
Montgomery	1770	18.80%	1.25%	15.39%	18.10%
Morgan	319	20.32%	5.98%	14.95%	14.41%
Morrow	266	12.41%	2.76%	15.50%	13.57%
Muskingum	337	15.63%	2.77%	15.24%	13.86%
Noble	261	16.05%	3.09%	14.66%	14.38%
Ottawa	316	14.84%	3.42%	14.91%	13.50%
Paulding	320	23.11%	6.39%	15.34%	12.44%
Perry	267	18.93%	4.21%	15.46%	13.86%
Pickaway	282	15.72%	3.20%	15.23%	16.89%
Pike	406	26.06%	4.60%	15.32%	16.66%
Portage	285	15.73%	2.46%	15.63%	14.09%
Preble	354	10.71%	2.06%	15.32%	12.95%
Putnam	306	7.17%	1.56%	15.22%	13.03%
Richland	341	12.94%	2.18%	15.11%	13.57%
Ross	365	18.31%	3.02%	15.30%	16.89%
Sandusky	398	13.38%	2.51%	15.19%	13.30%
Scioto	462	19.07%	2.88%	15.10%	16.66%
Seneca	361	7.85%	1.80%	15.14%	13.30%
Shelby	326	12.19%	2.78%	15.42%	13.22%
Stark	1137	14.70%	1.30%	15.19%	14.38%
Summit	3346	15.32%	1.01%	15.37%	14.09%
Trumbull	617	12.87%	1.63%	15.06%	13.55%
Tuscarawas	556	12.66%	1.87%	15.15%	14.38%
Union	286	12.62%	3.07%	16.15%	14.10%
Van Wert	301	9.06%	2.44%	15.03%	12.44%
Vinton	235	18.86%	4.05%	15.40%	16.89%
Warren	748	12.06%	1.58%	15.88%	14.37%

Continued on next page

Table 13 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	13.41%	2.32%	15.17%	14.19%
Wayne	661	13.02%	2.09%	15.40%	13.45%
Williams	337	16.89%	3.41%	15.18%	12.44%
Wood	687	12.36%	1.74%	15.57%	13.03%
Wyandot	288	9.00%	2.09%	15.04%	13.30%
Total	50944				

Table 14: Comparing No Pay Bills Estimates

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Adams	490	21.43%	4.71%	26.21%	28.19%
Allen	394	14.85%	2.51%	25.92%	26.99%
Ashland	323	14.37%	3.03%	26.04%	22.85%
Ashtabula	403	12.88%	2.09%	25.98%	24.99%
Athens	336	15.44%	3.11%	27.18%	24.77%
Auglaize	272	13.91%	2.96%	25.99%	23.50%
Belmont	348	14.81%	2.68%	25.17%	23.71%
Brown	662	22.73%	3.19%	26.73%	28.19%
Butler	1284	14.42%	1.26%	27.08%	23.71%
Carroll	303	15.63%	4.18%	25.97%	23.71%
Champaign	314	14.12%	3.13%	26.42%	23.71%
Clark	407	20.57%	2.52%	25.99%	23.71%
Clermont	1060	18.09%	1.69%	27.37%	25.56%
Clinton	293	23.99%	4.27%	26.63%	25.05%
Columbiana	466	17.40%	2.43%	25.84%	24.78%
Coshocton	376	12.42%	2.24%	25.84%	23.25%
Crawford	291	13.90%	3.10%	25.80%	24.02%
Cuyahoga	4103	13.90%	0.71%	26.08%	25.31%
Darke	469	11.82%	2.26%	25.73%	22.15%
Defiance	337	12.12%	2.59%	26.26%	22.15%
Delaware	335	16.23%	2.43%	27.73%	23.14%
Erie	407	10.97%	2.05%	25.75%	22.85%
Fairfield	288	14.28%	2.49%	26.76%	23.14%
Fayette	279	8.95%	2.08%	26.08%	25.05%
Franklin	3118	18.20%	0.89%	27.55%	27.44%
Fulton	266	10.05%	2.58%	26.34%	23.59%
Gallia	310	21.81%	4.12%	26.22%	26.52%
Geauga	262	12.25%	2.46%	26.31%	24.99%
Greene	350	11.82%	2.04%	26.67%	23.71%
Guernsey	290	23.70%	4.63%	25.97%	24.77%
Hamilton	2266	13.18%	0.90%	26.51%	21.90%
Hancock	396	14.25%	2.64%	26.41%	22.97%
Hardin	280	13.81%	2.65%	26.28%	23.57%
Harrison	262	22.76%	5.49%	25.27%	23.85%
Henry	303	11.00%	3.11%	26.07%	22.80%
Highland	634	18.54%	3.27%	26.13%	27.76%
Hocking	269	20.84%	4.79%	26.19%	25.46%
Holmes	326	12.21%	3.88%	26.64%	22.85%
Huron	402	19.05%	3.44%	26.49%	24.02%
Jackson	307	18.73%	3.68%	26.30%	25.68%
Jefferson	338	13.90%	2.80%	25.18%	22.11%

Continued on next page

Table 14 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Knox	327	15.31%	3.14%	26.16%	23.14%
Lake	377	13.29%	1.90%	26.23%	24.08%
Lawrence	359	22.36%	3.41%	26.12%	28.57%
Licking	286	12.97%	2.23%	26.66%	23.14%
Logan	296	12.19%	3.20%	26.09%	23.57%
Lorain	1878	13.50%	1.32%	26.52%	22.85%
Lucas	1857	18.37%	1.33%	26.53%	31.19%
Madison	280	17.26%	3.43%	26.44%	26.30%
Mahoning	1324	15.71%	1.52%	25.34%	21.78%
Marion	398	15.30%	2.87%	26.10%	22.97%
Medina	251	11.67%	2.18%	26.97%	22.85%
Meigs	480	17.94%	3.76%	25.91%	26.51%
Mercer	329	7.24%	2.32%	25.81%	22.15%
Miami	332	15.21%	2.74%	26.28%	23.71%
Monroe	232	19.43%	7.16%	25.41%	22.11%
Montgomery	1770	18.80%	1.25%	26.39%	25.79%
Morgan	319	20.32%	5.98%	25.60%	24.77%
Morrow	266	12.41%	2.76%	26.61%	23.14%
Muskingum	337	15.63%	2.77%	26.12%	24.77%
Noble	261	16.05%	3.09%	25.54%	24.77%
Ottawa	316	14.84%	3.42%	25.44%	22.85%
Paulding	320	23.11%	6.39%	26.33%	22.15%
Perry	267	18.93%	4.21%	26.55%	23.97%
Pickaway	282	15.72%	3.20%	26.36%	27.44%
Pike	406	26.06%	4.60%	26.29%	27.64%
Portage	285	15.73%	2.46%	26.97%	24.95%
Preble	354	10.71%	2.06%	26.25%	23.45%
Putnam	306	7.17%	1.56%	26.12%	22.97%
Richland	341	12.94%	2.18%	25.95%	24.02%
Ross	365	18.31%	3.02%	26.37%	27.44%
Sandusky	398	13.38%	2.51%	26.01%	24.07%
Scioto	462	19.07%	2.88%	25.93%	28.19%
Seneca	361	7.85%	1.80%	25.99%	22.97%
Shelby	326	12.19%	2.78%	26.49%	25.79%
Stark	1137	14.70%	1.30%	25.97%	23.85%
Summit	3346	15.32%	1.01%	26.31%	25.31%
Trumbull	617	12.87%	1.63%	25.75%	24.78%
Tuscarawas	556	12.66%	1.87%	25.94%	24.77%
Union	286	12.62%	3.07%	27.66%	23.23%
Van Wert	301	9.06%	2.44%	25.74%	22.15%
Vinton	235	18.86%	4.05%	26.45%	27.16%
Warren	748	12.06%	1.58%	27.31%	23.71%

Continued on next page

Table 14 – continued from previous page

County	N	Survey-Weighted		Synthetic	Smoothed
		Estimate	SE	Estimate	Estimate
Washington	378	13.41%	2.32%	25.96%	23.71%
Wayne	661	13.02%	2.09%	26.44%	23.25%
Williams	337	16.89%	3.41%	26.05%	22.15%
Wood	687	12.36%	1.74%	26.93%	22.97%
Wyandot	288	9.00%	2.09%	25.77%	22.97%
Total	50944				

Figure 1:

Confidence Intervals for County Effects (High Blood Pressure)

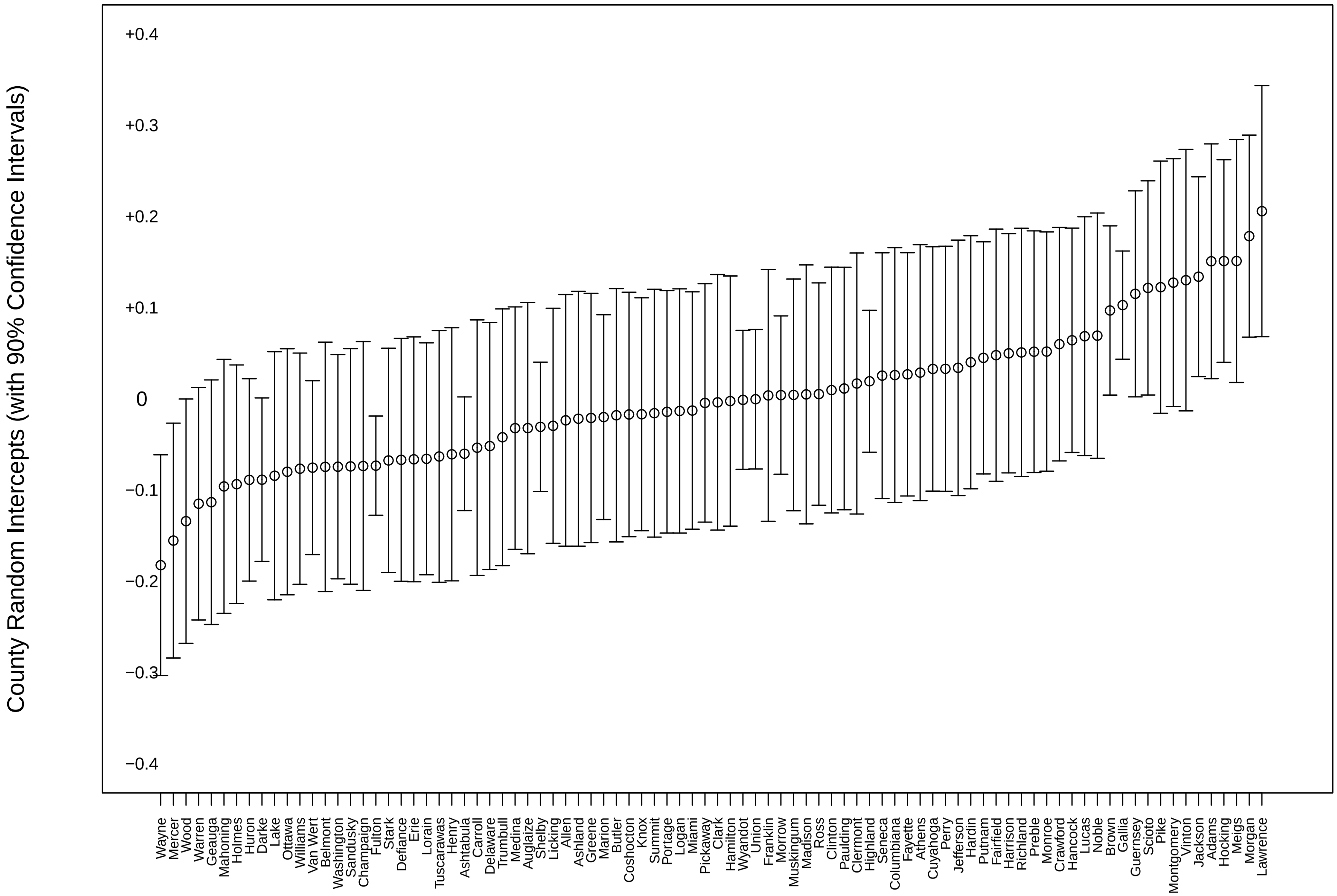


Figure 2:

Confidence Intervals for County Effects (Heart Attack)

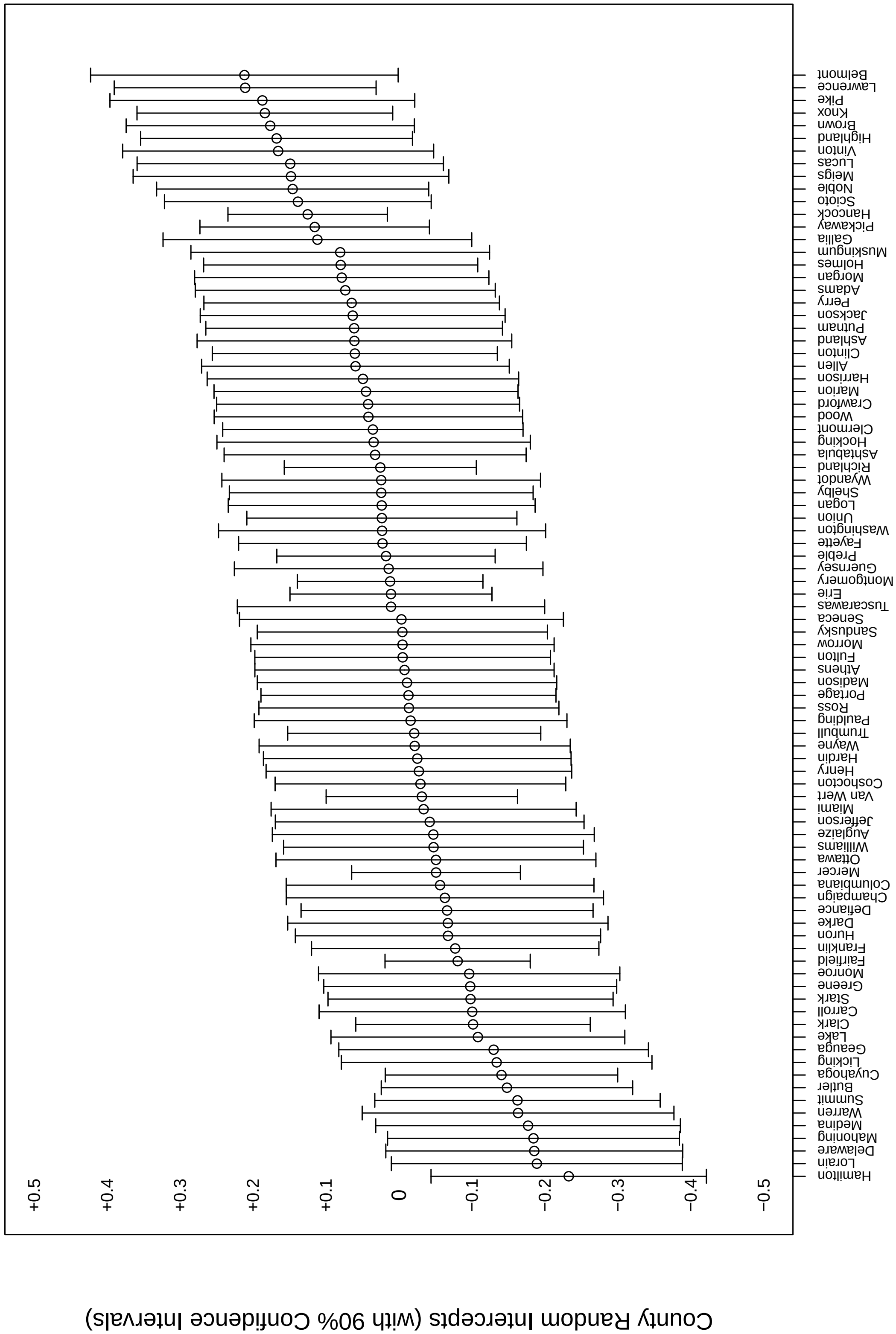


Figure 3:

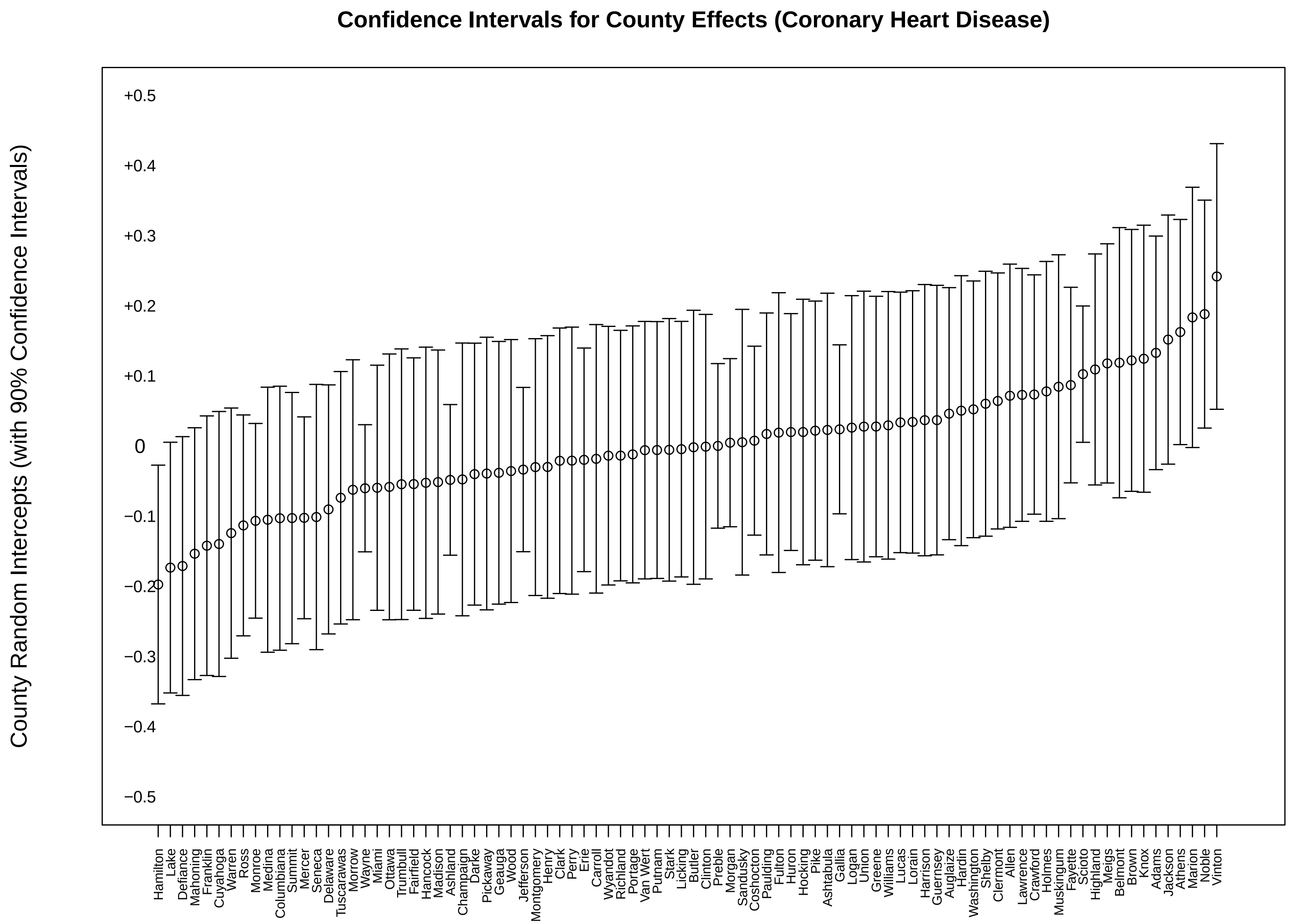

Confidence Intervals for County Effects (Coronary Heart Disease)
County Random Intercepts (with 90% Confidence Intervals)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Hamilton
Lake
Defiance
Mahoning
Franklin
Cuyahoga
Warren
Ross
Monroe
Medina
Columbiana
Summit
Mercer
Seneca
Delaware
Tuscarawas
Morrow
Wayne
Miami
Ottawa
Trumbull
Fairfield
Hancock
Madison
Ashland
Champaign
Darke
Pickaway
Geauga
Wood
Jefferson
Montgomery
Henry
Clark
Perry
Erie
Carroll
Wyandot
Richland
Portage
Van Wert
Putnam
Stark
Licking
Butler
Clinton
Preble
Morgan
Sandusky
Coshocton
Paulding
Fulton
Huron
Hocking
Pike
Ashtabula
Gallia
Logan
Union
Greene
Williams
Lucas
Lorain
Harrison
Guernsey
Auglaize
Hardin
Washington
Shelby
Clermont
Allen
Lawrence
Crawford
Holmes
Muskingum
Fayette
Scioto
Highland
Meigs
Belmont
Brown
Knox
Adams
Jackson
Athens
Marion
Noble
Vinton

Figure 4:

Confidence Intervals for County Effects (Stroke)

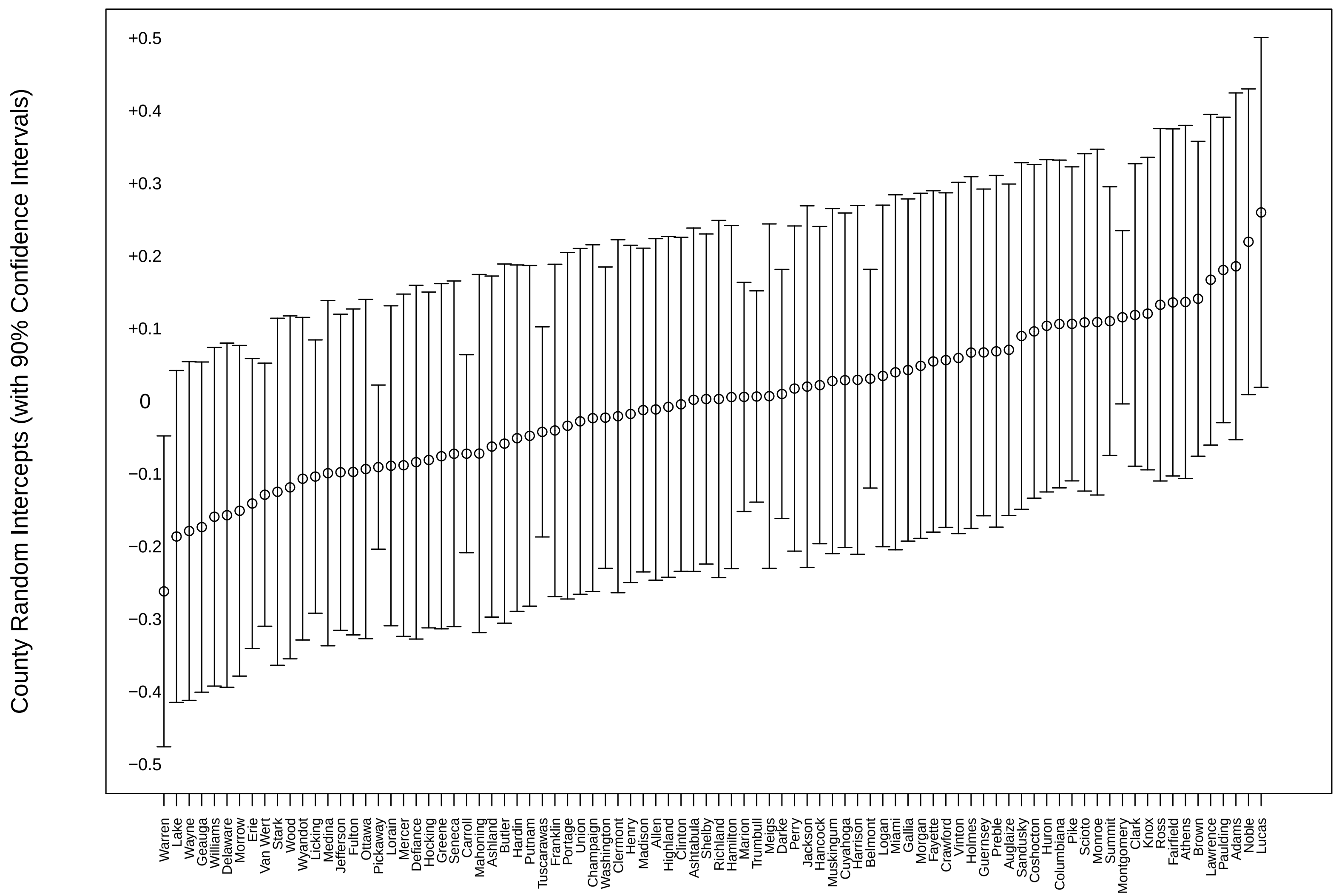


Figure 5:

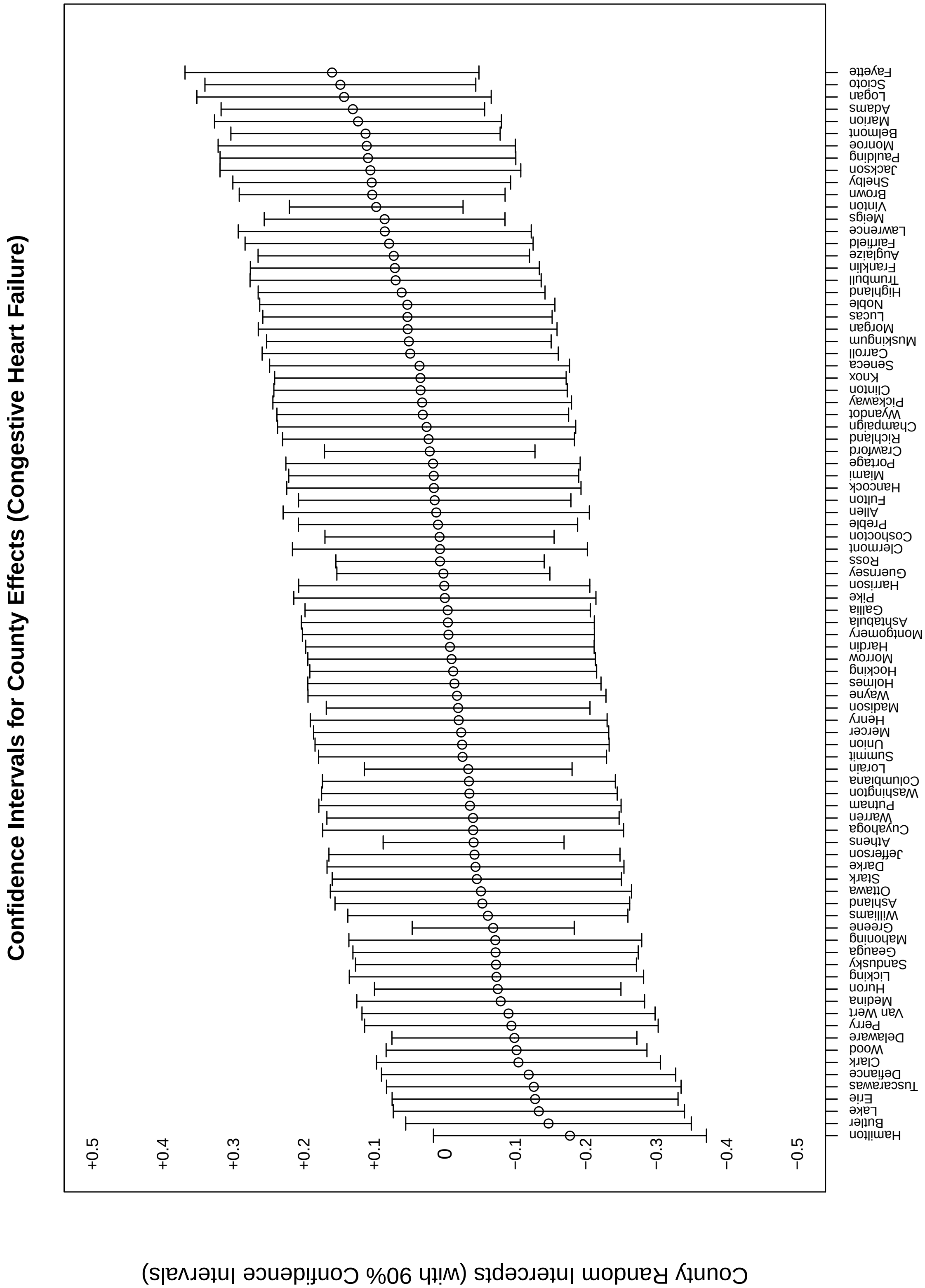
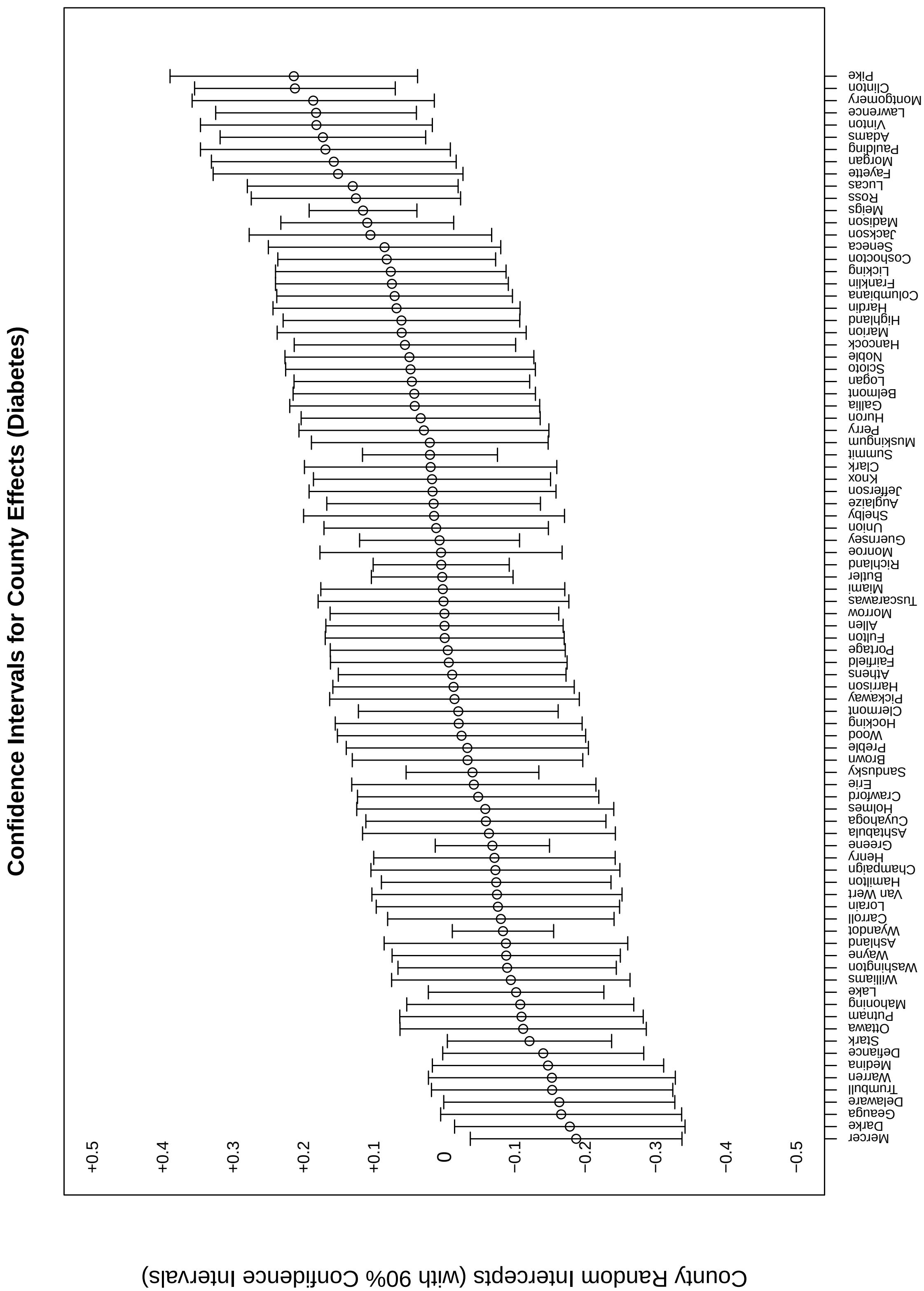
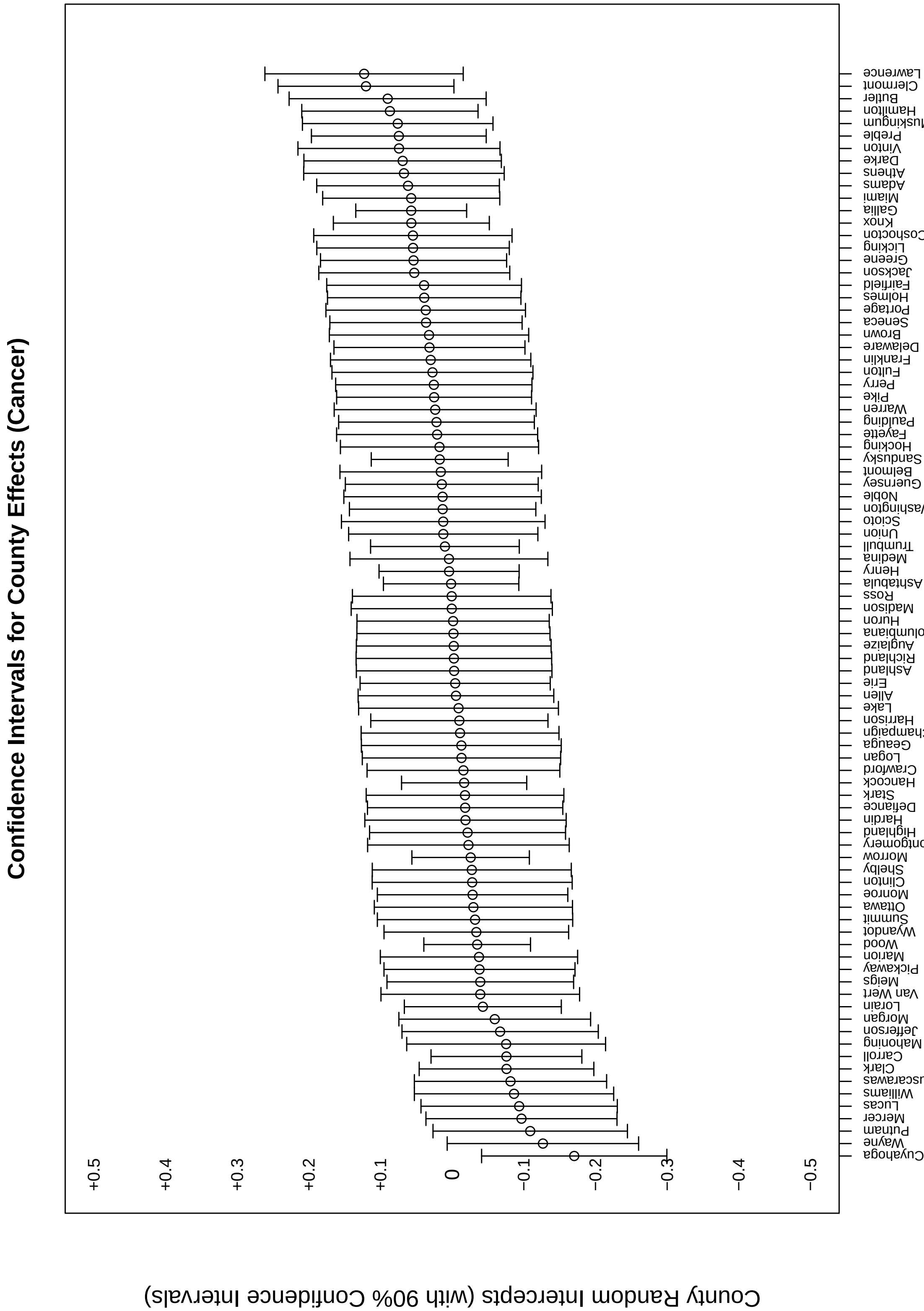

Confidence Intervals for County Effects (Congestive Heart Failure)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Hamilton
Butler
Lake
Erie
Tuscarawas
Defiance
Clark
Wood
Delaware
Perry
Van Wert
Medina
Huron
Licking
Sandusky
Geauga
Mahoning
Greene
Williams
Ashland
Ottawa
Stark
Darke
Jefferson
Athens
Cuyahoga
Warren
Putnam
Washington
Columbiana
Lorain
Summit
Union
Mercer
Henry
Madison
Wayne
Holmes
Hocking
Morrow
Hardin
Montgomery
Ashtabula
Gallia
Pike
Harrison
Guernsey
Ross
Clermont
Coshocton
Preble
Allen
Fulton
Hancock
Miami
Portage
Crawford
Richland
Champaign
Wyandot
Pickaway
Clinton
Knox
Seneca
Carroll
Muskingum
Morgan
Lucas
Noble
Highland
Trumbull
Franklin
Auglaize
Fairfield
Lawrence
Meigs
Vinton
Brown
Shelby
Jackson
Paulding
Monroe
Belmont
Marion
Adams
Logan
Scioto
Fayette
County Random Intercepts (with 90% Confidence Intervals)

Figure 6:



Confidence Intervals for County Effects (Diabetes)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Mercer
Darke
Geauga
Delaware
Trumbull
Warren
Medina
Defiance
Stark
Ottawa
Putnam
Mahoning
Lake
Williams
Washington
Wayne
Ashland
Wyandot
Carroll
Lorain
Van Wert
Hamilton
Champaign
Henry
Greene
Ashtabula
Cuyahoga
Holmes
Crawford
Erie
Sandusky
Brown
Preble
Wood
Hocking
Clermont
Pickaway
Harrison
Athens
Fairfield
Portage
Fulton
Allen
Morrow
Tuscarawas
Miami
Butler
Richland
Monroe
Guernsey
Union
Shelby
Auglaize
Jefferson
Knox
Clark
Summit
Muskingum
Perry
Huron
Gallia
Belmont
Logan
Scioto
Noble
Hancock
Marion
Highland
Hardin
Columbiana
Franklin
Licking
Coshocton
Seneca
Jackson
Madison
Meigs
Ross
Lucas
Fayette
Morgan
Paulding
Adams
Vinton
Lawrence
Montgomery
Clinton
Pike
County Random Intercepts (with 90% Confidence Intervals)

Figure 7:



Confidence Intervals for County Effects (Cancer)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Cuyahoga
Wayne
Putnam
Mercer
Lucas
Williams
Tuscarawas
Clark
Carroll
Mahoning
Jefferson
Morgan
Lorain
Van Wert
Meigs
Pickaway
Marion
Wood
Wyandot
Summit
Ottawa
Monroe
Clinton
Shelby
Morrow
Montgomery
Highland
Hardin
Defiance
Stark
Hancock
Crawford
Logan
Geauga
Champaign
Harrison
Lake
Allen
Erie
Ashland
Richland
Auglaize
Columbiana
Huron
Madison
Ross
Ashtabula
Henry
Medina
Trumbull
Union
Scioto
Washington
Noble
Guernsey
Belmont
Sandusky
Hocking
Fayette
Paulding
Warren
Pike
Perry
Fulton
Franklin
Delaware
Brown
Seneca
Portage
Holmes
Fairfield
Jackson
Greene
Licking
Coshocton
Knox
Gallia
Miami
Adams
Athens
Darke
Vinton
Preble
Muskingum
Hamilton
Butler
Clermont
Lawrence
County Random Intercepts (with 90% Confidence Intervals)

Figure 8:

Confidence Intervals for County Effects (Obesity)

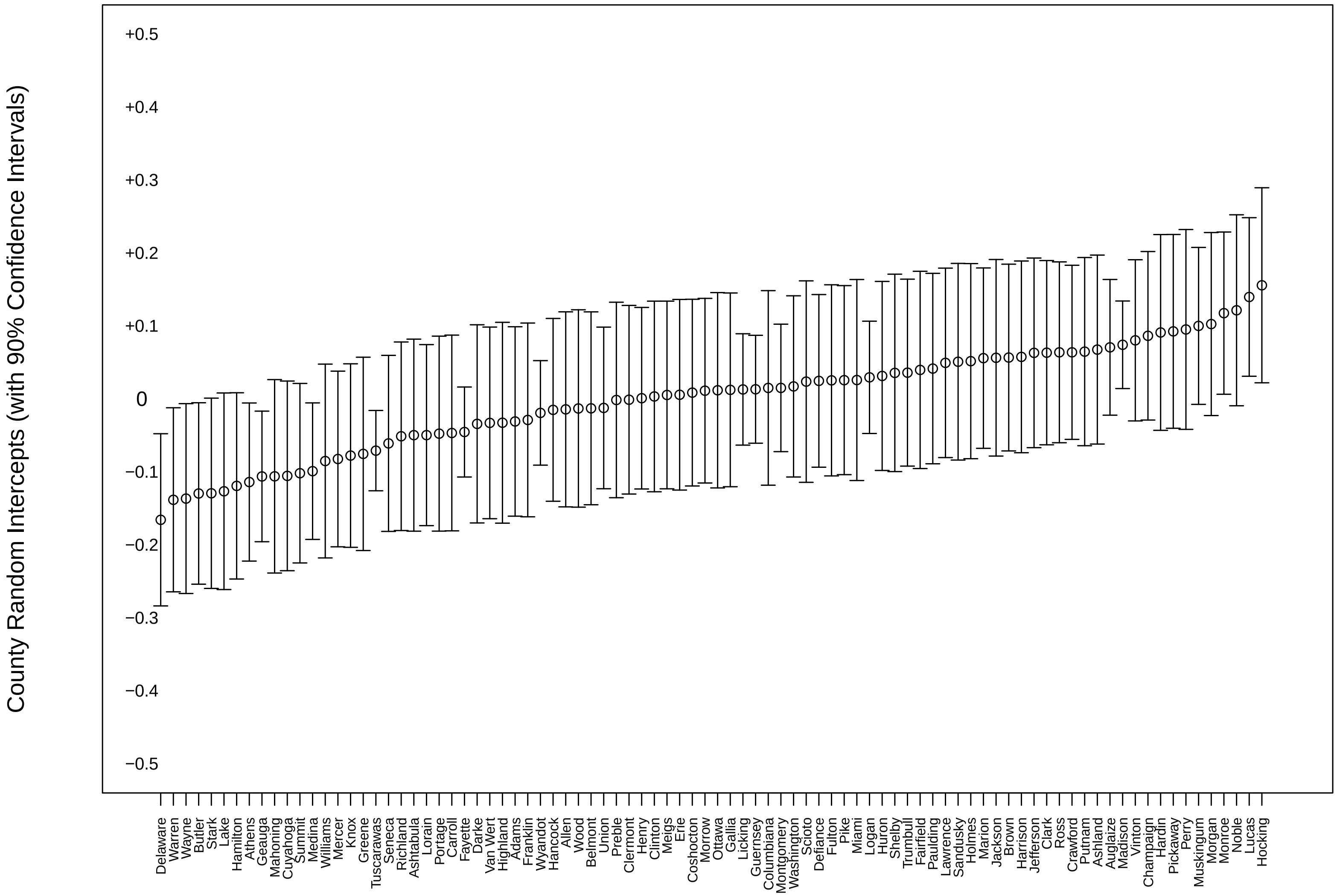


Figure 9:

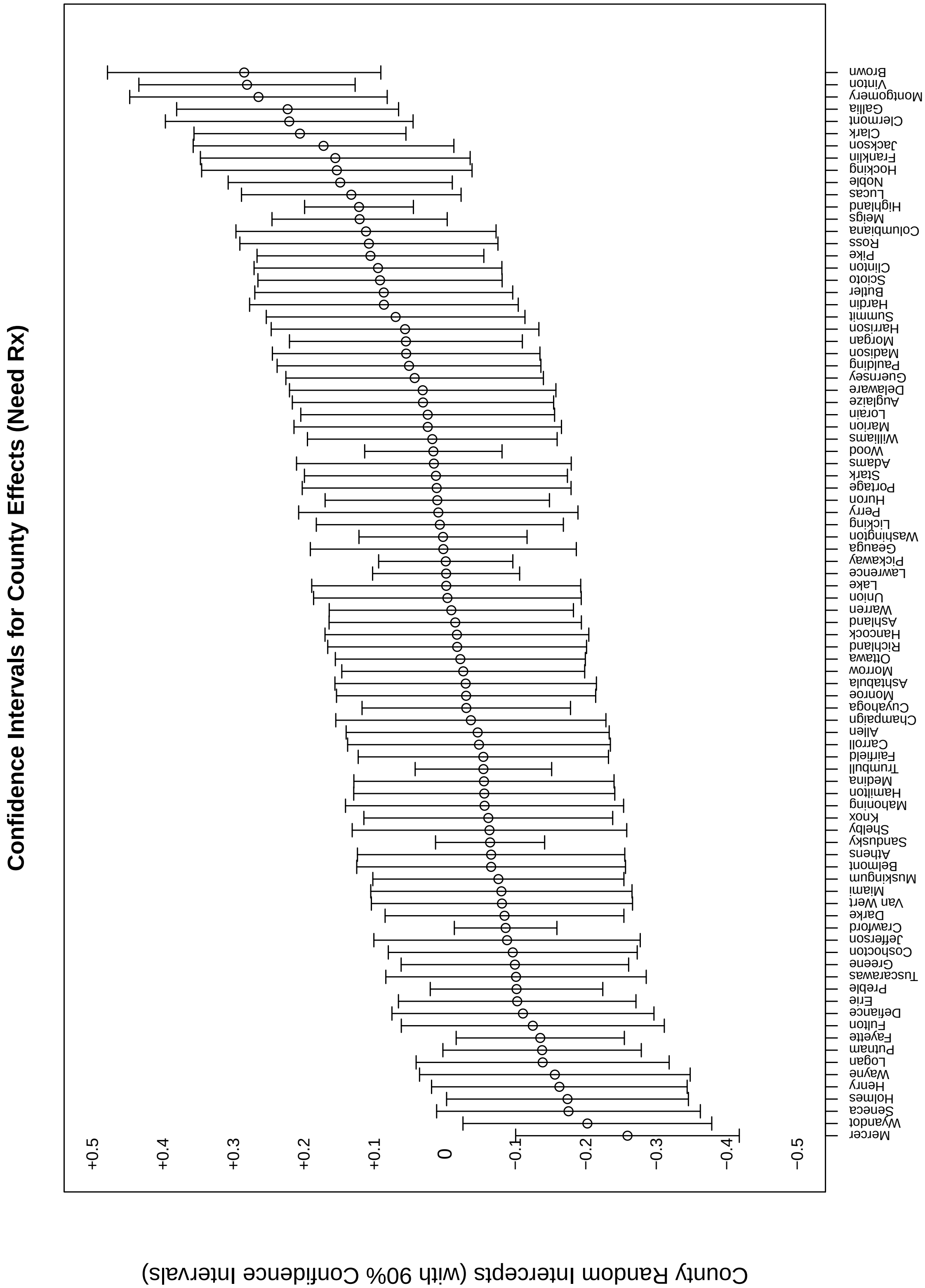
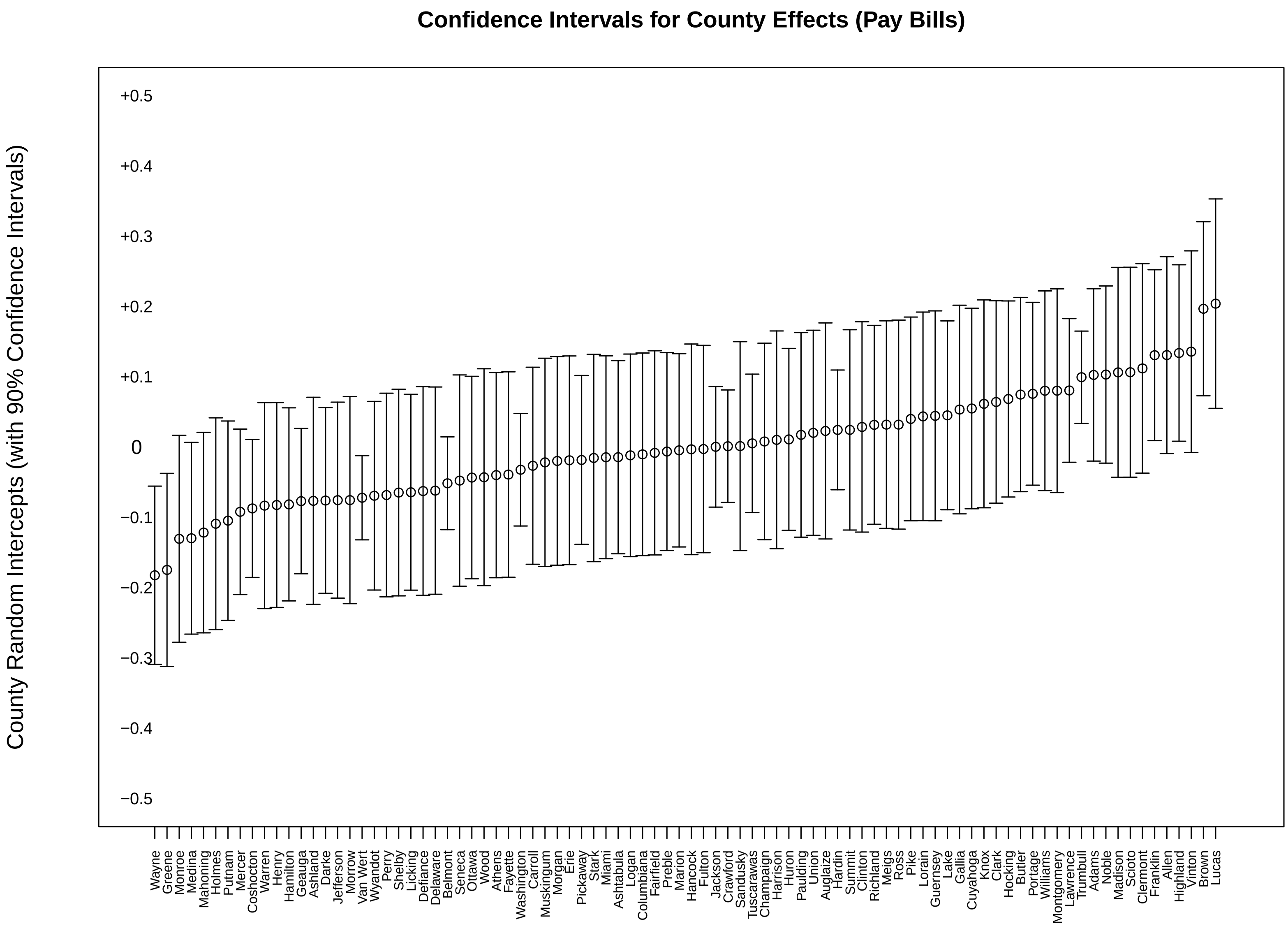

Confidence Intervals for County Effects (Need Rx)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Mercer
Wyandot
Seneca
Holmes
Henry
Wayne
Logan
Putnam
Fayette
Fulton
Defiance
Erie
Preble
Tuscarawas
Greene
Coshocton
Jefferson
Crawford
Darke
Van Wert
Miami
Muskingum
Belmont
Athens
Sandusky
Shelby
Knox
Mahoning
Hamilton
Medina
Trumbull
Fairfield
Carroll
Allen
Champaign
Cuyahoga
Monroe
Ashtabula
Morrow
Ottawa
Richland
Hancock
Ashland
Warren
Union
Lake
Lawrence
Pickaway
Geauga
Washington
Licking
Perry
Huron
Portage
Stark
Adams
Wood
Williams
Marion
Lorain
Auglaize
Delaware
Guernsey
Paulding
Madison
Morgan
Harrison
Summit
Hardin
Butler
Scioto
Clinton
Pike
Ross
Columbiana
Meigs
Highland
Lucas
Noble
Hocking
Franklin
Jackson
Clark
Clermont
Gallia
Montgomery
Vinton
Brown
County Random Intercepts (with 90% Confidence Intervals)

Figure 10:


Confidence Intervals for County Effects (Pay Bills)
County Random Intercepts (with 90% Confidence Intervals)
+0.5
+0.4
+0.3
+0.2
+0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
Wayne
Greene
Monroe
Medina
Mahoning
Holmes
Putnam
Mercer
Coshocton
Warren
Henry
Hamilton
Geauga
Ashland
Darke
Jefferson
Morrow
Van Wert
Wyandot
Perry
Shelby
Licking
Defiance
Delaware
Belmont
Seneca
Ottawa
Wood
Athens
Fayette
Washington
Carroll
Muskingum
Morgan
Erie
Pickaway
Stark
Miami
Ashtabula
Logan
Columbiana
Fairfield
Preble
Marion
Hancock
Fulton
Jackson
Crawford
Sandusky
Tuscarawas
Champaign
Harrison
Huron
Paulding
Union
Auglaize
Hardin
Summit
Clinton
Richland
Meigs
Ross
Pike
Lorain
Guernsey
Lake
Gallia
Cuyahoga
Knox
Clark
Hocking
Butler
Portage
Williams
Montgomery
Lawrence
Trumbull
Adams
Noble
Madison
Scioto
Clermont
Franklin
Allen
Highland
Vinton
Brown
Lucas

Appendix

TEXT about the estimation code, as well as where gllamm may be downloaded from.

The Stata routines for Generalized Linear Latent and Mixed Models *gllamm* were authored by Sophia Rabe-Hesketh as part of joint work with Anders Skrondal and Andrew Pickles. All code, documentation, and ancillary materials may be downloaded from `http://www.gllamm.org/`.

Table A.1: Comparing High Blood Pressure Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.15	0.07	0.17	0.08
Allen	394	-0.02	0.08	-0.04	0.08
Ashland	323	-0.02	0.08	0.04	0.09
Ashtabula	403	-0.06	0.08	-0.06	0.08
Athens	336	0.03	0.08	-0.03	0.09
Auglaize	272	-0.03	0.08	0.00	0.09
Belmont	348	-0.07	0.08	0.02	0.08
Brown	662	0.10	0.07	0.11	0.07
Butler	1284	-0.02	0.05	-0.15	0.05
Carroll	303	-0.05	0.08	-0.04	0.09
Champaign	314	-0.07	0.08	-0.06	0.09
Clark	407	0.00	0.08	0.02	0.08
Clermont	1060	0.02	0.06	-0.07	0.06
Clinton	293	0.01	0.08	0.04	0.09
Columbiana	466	0.03	0.07	0.04	0.08
Coshocton	376	-0.02	0.08	0.04	0.08
Crawford	291	0.06	0.08	0.15	0.09
Cuyahoga	4103	0.03	0.03	-0.01	0.03
Darke	469	-0.09	0.07	-0.08	0.08
Defiance	337	-0.07	0.08	-0.07	0.09
Delaware	335	-0.05	0.08	-0.18	0.09
Erie	407	-0.07	0.08	-0.07	0.08
Fairfield	288	0.05	0.08	0.00	0.09
Fayette	279	0.03	0.08	0.05	0.09
Franklin	3118	0.00	0.04	-0.16	0.04
Fulton	266	-0.07	0.09	-0.14	0.09
Gallia	310	0.10	0.08	0.14	0.09
Geauga	262	-0.11	0.09	-0.16	0.09
Greene	350	-0.02	0.08	-0.11	0.09
Guernsey	290	0.12	0.08	0.17	0.09
Hamilton	2266	0.00	0.04	-0.06	0.04
Hancock	396	0.06	0.08	0.01	0.08
Hardin	280	0.04	0.08	0.11	0.09
Harrison	262	0.05	0.08	0.14	0.09
Henry	303	-0.06	0.08	-0.10	0.09
Highland	634	0.02	0.07	0.06	0.07
Hocking	269	0.15	0.08	0.20	0.09
Holmes	326	-0.09	0.08	-0.09	0.09
Huron	402	-0.09	0.08	-0.07	0.08
Jackson	307	0.13	0.08	0.21	0.09

Continued on next page

Table A.1 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	0.03	0.08	0.09	0.09
Knox	327	-0.02	0.08	-0.01	0.09
Lake	377	-0.08	0.08	-0.13	0.08
Lawrence	359	0.21	0.08	0.26	0.08
Licking	286	-0.03	0.09	-0.16	0.09
Logan	296	-0.01	0.08	-0.01	0.09
Lorain	1878	-0.07	0.05	-0.09	0.04
Lucas	1857	0.07	0.05	0.01	0.04
Madison	280	0.00	0.08	0.06	0.09
Mahoning	1324	-0.10	0.05	-0.02	0.05
Marion	398	-0.02	0.08	0.05	0.08
Medina	251	-0.03	0.09	-0.13	0.09
Meigs	480	0.15	0.07	0.21	0.08
Mercer	329	-0.16	0.08	-0.20	0.09
Miami	332	-0.01	0.08	0.04	0.09
Monroe	232	0.05	0.09	0.15	0.09
Montgomery	1770	0.13	0.05	0.12	0.05
Morgan	319	0.18	0.08	0.20	0.09
Morrow	266	0.00	0.08	0.02	0.09
Muskingum	337	0.00	0.08	-0.02	0.09
Noble	261	0.07	0.09	0.06	0.09
Ottawa	316	-0.08	0.08	-0.02	0.09
Paulding	320	0.01	0.08	0.02	0.09
Perry	267	0.03	0.09	0.04	0.09
Pickaway	282	0.00	0.08	-0.02	0.09
Pike	406	0.12	0.08	0.14	0.08
Portage	285	-0.01	0.08	-0.06	0.09
Preble	354	0.05	0.08	0.09	0.08
Putnam	306	0.05	0.08	0.04	0.09
Richland	341	0.05	0.08	0.12	0.08
Ross	365	0.01	0.08	-0.04	0.08
Sandusky	398	-0.07	0.08	-0.09	0.08
Scioto	462	0.12	0.07	0.18	0.08
Seneca	361	0.03	0.08	0.04	0.08
Shelby	326	-0.03	0.08	-0.09	0.09
Stark	1137	-0.07	0.06	-0.08	0.06
Summit	3346	-0.02	0.04	-0.02	0.03
Trumbull	617	-0.04	0.07	-0.02	0.07
Tuscarawas	556	-0.06	0.07	-0.06	0.07
Union	286	0.00	0.08	-0.07	0.09
Van Wert	301	-0.08	0.08	-0.04	0.09

Continued on next page

Table A.1 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.13	0.09	0.18	0.09
Warren	748	-0.11	0.07	-0.27	0.07
Washington	378	-0.07	0.08	0.00	0.08
Wayne	661	-0.18	0.07	-0.13	0.07
Williams	337	-0.08	0.08	-0.10	0.09
Wood	687	-0.13	0.07	-0.18	0.07
Wyandot	288	0.00	0.08	0.02	0.09
Total	50944				

Table A.2: Comparing Heart Attack Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.07	0.11	0.12	0.13
Allen	394	0.06	0.12	0.09	0.14
Ashland	323	0.06	0.12	0.14	0.14
Ashtabula	403	0.03	0.12	0.04	0.14
Athens	336	-0.01	0.13	-0.02	0.15
Auglaize	272	-0.05	0.13	-0.03	0.15
Belmont	348	0.21	0.12	0.34	0.13
Brown	662	0.18	0.10	0.25	0.11
Butler	1284	-0.15	0.10	-0.27	0.10
Carroll	303	-0.10	0.13	-0.13	0.15
Champaign	314	-0.06	0.13	-0.10	0.15
Clark	407	-0.10	0.12	-0.11	0.14
Clermont	1060	0.04	0.10	-0.04	0.10
Clinton	293	0.06	0.13	0.09	0.15
Columbiana	466	-0.06	0.12	-0.05	0.13
Coshocton	376	-0.03	0.12	0.02	0.14
Crawford	291	0.04	0.13	0.14	0.15
Cuyahoga	4103	-0.14	0.06	-0.17	0.06
Darke	469	-0.07	0.12	-0.09	0.14
Defiance	337	-0.07	0.13	-0.09	0.15
Delaware	335	-0.19	0.13	-0.36	0.16
Erie	407	0.01	0.12	0.01	0.14
Fairfield	288	-0.08	0.13	-0.15	0.15
Fayette	279	0.02	0.13	0.07	0.15
Franklin	3118	-0.08	0.07	-0.25	0.07
Fulton	266	-0.01	0.13	-0.07	0.15
Gallia	310	0.11	0.12	0.19	0.14
Geauga	262	-0.13	0.13	-0.21	0.16
Greene	350	-0.10	0.13	-0.17	0.15
Guernsey	290	0.01	0.13	0.07	0.15
Hamilton	2266	-0.23	0.08	-0.30	0.08
Hancock	396	0.13	0.12	0.14	0.13
Hardin	280	-0.03	0.13	0.05	0.15
Harrison	262	0.05	0.13	0.12	0.15
Henry	303	-0.03	0.13	-0.06	0.15
Highland	634	0.17	0.11	0.24	0.11
Hocking	269	0.03	0.13	0.04	0.15
Holmes	326	0.08	0.12	0.12	0.14
Huron	402	-0.07	0.12	-0.08	0.14
Jackson	307	0.06	0.12	0.15	0.14

Continued on next page

Table A.2 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.04	0.12	-0.01	0.14
Knox	327	0.18	0.12	0.25	0.14
Lake	377	-0.11	0.13	-0.17	0.15
Lawrence	359	0.21	0.12	0.27	0.13
Licking	286	-0.13	0.13	-0.27	0.16
Logan	296	0.02	0.13	0.04	0.15
Lorain	1878	-0.19	0.08	-0.25	0.09
Lucas	1857	0.15	0.08	0.10	0.08
Madison	280	-0.01	0.13	0.02	0.15
Mahoning	1324	-0.18	0.09	-0.15	0.10
Marion	398	0.05	0.12	0.10	0.14
Medina	251	-0.18	0.14	-0.30	0.16
Meigs	480	0.15	0.11	0.25	0.12
Mercer	329	-0.05	0.13	-0.08	0.15
Miami	332	-0.03	0.13	-0.04	0.15
Monroe	232	-0.10	0.13	-0.08	0.16
Montgomery	1770	0.01	0.08	0.01	0.08
Morgan	319	0.08	0.13	0.11	0.14
Morrow	266	0.00	0.13	0.00	0.15
Muskingum	337	0.08	0.13	0.10	0.14
Noble	261	0.15	0.13	0.21	0.15
Ottawa	316	-0.05	0.13	-0.01	0.15
Paulding	320	-0.02	0.13	0.00	0.15
Perry	267	0.06	0.13	0.09	0.15
Pickaway	282	0.12	0.13	0.15	0.15
Pike	406	0.19	0.12	0.23	0.13
Portage	285	-0.01	0.13	-0.05	0.15
Preble	354	0.02	0.12	0.05	0.14
Putnam	306	0.06	0.13	0.09	0.15
Richland	341	0.03	0.12	0.09	0.14
Ross	365	-0.01	0.12	-0.03	0.14
Sandusky	398	0.00	0.12	-0.01	0.14
Scioto	462	0.14	0.11	0.23	0.13
Seneca	361	0.00	0.12	0.00	0.14
Shelby	326	0.02	0.13	-0.03	0.15
Stark	1137	-0.10	0.10	-0.11	0.10
Summit	3346	-0.16	0.07	-0.20	0.07
Trumbull	617	-0.02	0.11	-0.02	0.12
Tuscarawas	556	0.01	0.11	0.02	0.13
Union	286	0.02	0.13	-0.03	0.15
Van Wert	301	-0.03	0.13	-0.01	0.15

Continued on next page

Table A.2 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.17	0.13	0.27	0.15
Warren	748	-0.16	0.11	-0.30	0.12
Washington	378	0.02	0.12	0.11	0.14
Wayne	661	-0.02	0.11	0.06	0.12
Williams	337	-0.05	0.13	-0.07	0.15
Wood	687	0.04	0.11	-0.01	0.12
Wyandot	288	0.02	0.13	0.05	0.15
Total	50944				

Table A.3: Comparing Coronary Heart Disease Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.13	0.10	0.16	0.11
Allen	394	0.07	0.11	0.10	0.12
Ashland	323	-0.05	0.11	0.00	0.13
Ashtabula	403	0.02	0.11	0.03	0.12
Athens	336	0.16	0.11	0.16	0.12
Auglaize	272	0.05	0.11	0.10	0.13
Belmont	348	0.12	0.11	0.21	0.12
Brown	662	0.12	0.10	0.16	0.10
Butler	1284	0.00	0.08	-0.10	0.09
Carroll	303	-0.02	0.11	-0.02	0.13
Champaign	314	-0.05	0.11	-0.05	0.13
Clark	407	-0.02	0.11	-0.01	0.12
Clermont	1060	0.06	0.09	0.00	0.09
Clinton	293	0.00	0.11	0.01	0.13
Columbiana	466	-0.10	0.11	-0.12	0.12
Coshocton	376	0.01	0.11	0.05	0.12
Crawford	291	0.07	0.11	0.15	0.13
Cuyahoga	4103	-0.14	0.06	-0.16	0.06
Darke	469	-0.04	0.11	-0.03	0.12
Defiance	337	-0.17	0.12	-0.22	0.13
Delaware	335	-0.09	0.12	-0.20	0.13
Erie	407	-0.02	0.11	-0.02	0.12
Fairfield	288	-0.05	0.12	-0.10	0.13
Fayette	279	0.09	0.11	0.14	0.13
Franklin	3118	-0.14	0.07	-0.31	0.07
Fulton	266	0.02	0.12	-0.01	0.13
Gallia	310	0.02	0.11	0.05	0.13
Geauga	262	-0.04	0.12	-0.06	0.14
Greene	350	0.03	0.11	-0.02	0.13
Guernsey	290	0.04	0.11	0.09	0.13
Hamilton	2266	-0.20	0.07	-0.24	0.07
Hancock	396	-0.05	0.11	-0.08	0.12
Hardin	280	0.05	0.11	0.12	0.13
Harrison	262	0.04	0.12	0.10	0.13
Henry	303	-0.03	0.12	-0.05	0.13
Highland	634	0.11	0.10	0.15	0.10
Hocking	269	0.02	0.12	0.03	0.13
Holmes	326	0.08	0.11	0.11	0.13
Huron	402	0.02	0.11	0.04	0.12
Jackson	307	0.15	0.11	0.24	0.12

Continued on next page

Table A.3 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.03	0.11	0.01	0.13
Knox	327	0.12	0.11	0.17	0.12
Lake	377	-0.17	0.11	-0.24	0.13
Lawrence	359	0.07	0.11	0.09	0.12
Licking	286	0.00	0.12	-0.08	0.13
Logan	296	0.03	0.11	0.04	0.13
Lorain	1878	0.03	0.07	0.01	0.07
Lucas	1857	0.03	0.07	-0.02	0.07
Madison	280	-0.05	0.12	-0.02	0.13
Mahoning	1324	-0.15	0.08	-0.11	0.09
Marion	398	0.18	0.10	0.29	0.12
Medina	251	-0.10	0.12	-0.20	0.14
Meigs	480	0.12	0.10	0.18	0.11
Mercer	329	-0.10	0.12	-0.14	0.13
Miami	332	-0.06	0.11	-0.03	0.13
Monroe	232	-0.11	0.12	-0.09	0.14
Montgomery	1770	-0.03	0.07	-0.02	0.08
Morgan	319	0.01	0.11	-0.01	0.13
Morrow	266	-0.06	0.12	-0.07	0.14
Muskingum	337	0.08	0.11	0.08	0.13
Noble	261	0.19	0.12	0.22	0.13
Ottawa	316	-0.06	0.11	-0.02	0.13
Paulding	320	0.02	0.11	0.02	0.13
Perry	267	-0.02	0.12	-0.03	0.13
Pickaway	282	-0.04	0.12	-0.06	0.13
Pike	406	0.02	0.11	0.02	0.12
Portage	285	-0.01	0.12	-0.04	0.13
Preble	354	0.00	0.11	0.02	0.13
Putnam	306	-0.01	0.11	-0.01	0.13
Richland	341	-0.01	0.11	0.04	0.13
Ross	365	-0.11	0.11	-0.17	0.13
Sandusky	398	0.01	0.11	0.01	0.12
Scioto	462	0.10	0.10	0.17	0.11
Seneca	361	-0.10	0.11	-0.12	0.13
Shelby	326	0.06	0.11	0.03	0.13
Stark	1137	-0.01	0.08	-0.01	0.09
Summit	3346	-0.10	0.06	-0.12	0.06
Trumbull	617	-0.05	0.10	-0.04	0.11
Tuscarawas	556	-0.07	0.10	-0.09	0.11
Union	286	0.03	0.12	-0.01	0.13
Van Wert	301	-0.01	0.11	0.03	0.13

Continued on next page

Table A.3 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.24	0.12	0.34	0.13
Warren	748	-0.12	0.10	-0.25	0.11
Washington	378	0.05	0.11	0.12	0.12
Wayne	661	-0.06	0.10	-0.01	0.11
Williams	337	0.03	0.11	0.03	0.13
Wood	687	-0.04	0.10	-0.06	0.11
Wyandot	288	-0.01	0.12	0.00	0.13
Total	50944				

Table A.4: Comparing Stroke Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.19	0.13	0.20	0.14
Allen	394	-0.01	0.14	-0.01	0.15
Ashland	323	-0.06	0.14	-0.02	0.15
Ashtabula	403	0.00	0.14	0.01	0.15
Athens	336	0.14	0.14	0.12	0.15
Auglaize	272	0.07	0.14	0.11	0.15
Belmont	348	0.03	0.14	0.09	0.15
Brown	662	0.14	0.12	0.17	0.13
Butler	1284	-0.06	0.11	-0.13	0.11
Carroll	303	-0.07	0.15	-0.07	0.16
Champaign	314	-0.02	0.14	-0.01	0.15
Clark	407	0.12	0.14	0.15	0.14
Clermont	1060	-0.02	0.11	-0.07	0.12
Clinton	293	0.00	0.14	0.01	0.15
Columbiana	466	0.11	0.13	0.13	0.14
Coshocton	376	0.10	0.14	0.14	0.14
Crawford	291	0.06	0.14	0.11	0.15
Cuyahoga	4103	0.03	0.07	0.01	0.07
Darke	469	0.01	0.13	0.03	0.14
Defiance	337	-0.08	0.14	-0.08	0.15
Delaware	335	-0.16	0.15	-0.22	0.16
Erie	407	-0.14	0.14	-0.15	0.15
Fairfield	288	0.14	0.14	0.13	0.15
Fayette	279	0.05	0.14	0.07	0.15
Franklin	3118	-0.04	0.08	-0.18	0.08
Fulton	266	-0.10	0.15	-0.13	0.16
Gallia	310	0.04	0.14	0.06	0.15
Geauga	262	-0.17	0.15	-0.21	0.16
Greene	350	-0.08	0.15	-0.12	0.15
Guernsey	290	0.07	0.14	0.11	0.15
Hamilton	2266	0.01	0.09	-0.02	0.09
Hancock	396	0.02	0.14	0.01	0.15
Hardin	280	-0.05	0.15	-0.02	0.16
Harrison	262	0.03	0.14	0.07	0.16
Henry	303	-0.02	0.15	-0.02	0.15
Highland	634	-0.01	0.13	0.01	0.13
Hocking	269	-0.08	0.15	-0.09	0.16
Holmes	326	0.07	0.14	0.09	0.15
Huron	402	0.10	0.14	0.13	0.14
Jackson	307	0.02	0.14	0.04	0.15

Continued on next page

Table A.4 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.10	0.14	-0.08	0.15
Knox	327	0.12	0.14	0.15	0.15
Lake	377	-0.19	0.14	-0.21	0.15
Lawrence	359	0.17	0.14	0.18	0.14
Licking	286	-0.10	0.15	-0.15	0.16
Logan	296	0.03	0.14	0.05	0.15
Lorain	1878	-0.09	0.10	-0.10	0.10
Lucas	1857	0.26	0.09	0.21	0.09
Madison	280	-0.01	0.14	0.02	0.16
Mahoning	1324	-0.07	0.10	-0.03	0.11
Marion	398	0.01	0.14	0.05	0.15
Medina	251	-0.10	0.15	-0.14	0.16
Meigs	480	0.01	0.13	0.04	0.14
Mercer	329	-0.09	0.14	-0.10	0.15
Miami	332	0.04	0.14	0.08	0.15
Monroe	232	0.11	0.15	0.16	0.16
Montgomery	1770	0.12	0.09	0.13	0.09
Morgan	319	0.05	0.14	0.05	0.15
Morrow	266	-0.15	0.15	-0.16	0.16
Muskingum	337	0.03	0.14	0.01	0.15
Noble	261	0.22	0.14	0.24	0.15
Ottawa	316	-0.09	0.14	-0.06	0.15
Paulding	320	0.18	0.14	0.21	0.15
Perry	267	0.02	0.15	0.02	0.16
Pickaway	282	-0.09	0.15	-0.10	0.16
Pike	406	0.11	0.14	0.11	0.14
Portage	285	-0.03	0.15	-0.05	0.16
Preble	354	0.07	0.14	0.10	0.15
Putnam	306	-0.05	0.15	-0.05	0.15
Richland	341	0.00	0.14	0.05	0.15
Ross	365	0.13	0.14	0.13	0.15
Sandusky	398	0.09	0.14	0.10	0.14
Scioto	462	0.11	0.13	0.15	0.14
Seneca	361	-0.07	0.14	-0.06	0.15
Shelby	326	0.00	0.14	-0.03	0.15
Stark	1137	-0.12	0.11	-0.13	0.12
Summit	3346	0.11	0.07	0.09	0.07
Trumbull	617	0.01	0.13	0.03	0.13
Tuscarawas	556	-0.04	0.13	-0.03	0.14
Union	286	-0.03	0.15	-0.05	0.16
Van Wert	301	-0.13	0.15	-0.12	0.16

Continued on next page

Table A.4 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.06	0.15	0.08	0.16
Warren	748	-0.26	0.13	-0.34	0.14
Washington	378	-0.02	0.14	0.01	0.15
Wayne	661	-0.18	0.13	-0.15	0.14
Williams	337	-0.16	0.15	-0.18	0.16
Wood	687	-0.12	0.13	-0.14	0.13
Wyandot	288	-0.11	0.15	-0.11	0.16
Total	50944				

Table A.5: Comparing Congestive Heart Failure Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.13	0.12	0.22	0.14
Allen	394	0.01	0.12	0.03	0.16
Ashland	323	-0.05	0.13	-0.05	0.17
Ashtabula	403	0.00	0.12	0.00	0.16
Athens	336	-0.04	0.13	-0.09	0.17
Auglaize	272	0.07	0.13	0.15	0.17
Belmont	348	0.11	0.12	0.24	0.16
Brown	662	0.10	0.11	0.19	0.13
Butler	1284	-0.15	0.11	-0.28	0.13
Carroll	303	0.05	0.13	0.09	0.17
Champaign	314	0.03	0.13	0.05	0.17
Clark	407	-0.10	0.12	-0.16	0.16
Clermont	1060	0.01	0.11	-0.05	0.12
Clinton	293	0.03	0.13	0.07	0.17
Columbiana	466	-0.03	0.12	-0.04	0.16
Coshocton	376	0.01	0.12	0.05	0.16
Crawford	291	0.02	0.13	0.07	0.17
Cuyahoga	4103	-0.04	0.07	-0.05	0.07
Darke	469	-0.04	0.12	-0.05	0.16
Defiance	337	-0.12	0.13	-0.21	0.17
Delaware	335	-0.10	0.13	-0.26	0.17
Erie	407	-0.13	0.12	-0.22	0.16
Fairfield	288	0.08	0.13	0.11	0.17
Fayette	279	0.16	0.13	0.31	0.16
Franklin	3118	0.07	0.08	-0.04	0.08
Fulton	266	0.01	0.13	-0.01	0.17
Gallia	310	0.00	0.13	0.02	0.17
Geauga	262	-0.07	0.13	-0.16	0.18
Greene	350	-0.07	0.13	-0.16	0.17
Guernsey	290	0.00	0.13	0.05	0.17
Hamilton	2266	-0.18	0.09	-0.24	0.10
Hancock	396	0.02	0.12	0.00	0.16
Hardin	280	-0.01	0.13	0.03	0.17
Harrison	262	0.00	0.13	0.05	0.17
Henry	303	-0.02	0.13	-0.05	0.17
Highland	634	0.06	0.11	0.12	0.14
Hocking	269	-0.01	0.13	-0.01	0.17
Holmes	326	-0.01	0.13	-0.02	0.17
Huron	402	-0.08	0.12	-0.11	0.16
Jackson	307	0.11	0.12	0.24	0.16

Continued on next page

Table A.5 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.04	0.12	-0.01	0.16
Knox	327	0.03	0.13	0.06	0.16
Lake	377	-0.13	0.13	-0.24	0.17
Lawrence	359	0.09	0.12	0.17	0.16
Licking	286	-0.07	0.13	-0.18	0.17
Logan	296	0.14	0.13	0.26	0.16
Lorain	1878	-0.03	0.09	-0.08	0.10
Lucas	1857	0.05	0.09	0.06	0.10
Madison	280	-0.02	0.13	0.00	0.17
Mahoning	1324	-0.07	0.10	-0.04	0.12
Marion	398	0.12	0.12	0.24	0.15
Medina	251	-0.08	0.13	-0.21	0.18
Meigs	480	0.09	0.12	0.19	0.15
Mercer	329	-0.02	0.13	-0.06	0.17
Miami	332	0.02	0.13	0.05	0.16
Monroe	232	0.11	0.13	0.27	0.17
Montgomery	1770	-0.01	0.09	0.02	0.10
Morgan	319	0.05	0.13	0.09	0.16
Morrow	266	-0.01	0.13	-0.01	0.17
Muskingum	337	0.05	0.13	0.07	0.16
Noble	261	0.05	0.13	0.08	0.17
Ottawa	316	-0.05	0.13	-0.07	0.17
Paulding	320	0.11	0.13	0.17	0.16
Perry	267	-0.09	0.13	-0.16	0.18
Pickaway	282	0.03	0.13	0.06	0.17
Pike	406	0.00	0.12	0.02	0.16
Portage	285	0.02	0.13	0.00	0.17
Preble	354	0.01	0.12	0.02	0.16
Putnam	306	-0.04	0.13	-0.06	0.17
Richland	341	0.02	0.12	0.09	0.16
Ross	365	0.01	0.13	-0.01	0.16
Sandusky	398	-0.07	0.12	-0.13	0.16
Scioto	462	0.15	0.12	0.30	0.14
Seneca	361	0.04	0.12	0.07	0.16
Shelby	326	0.10	0.13	0.14	0.16
Stark	1137	-0.05	0.10	-0.06	0.12
Summit	3346	-0.03	0.07	-0.03	0.08
Trumbull	617	0.07	0.11	0.12	0.14
Tuscarawas	556	-0.13	0.12	-0.20	0.15
Union	286	-0.02	0.13	-0.09	0.17
Van Wert	301	-0.09	0.13	-0.14	0.17

Continued on next page

Table A.5 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.10	0.13	0.21	0.17
Warren	748	-0.04	0.12	-0.15	0.14
Washington	378	-0.03	0.12	-0.03	0.16
Wayne	661	-0.02	0.11	0.02	0.14
Williams	337	-0.06	0.13	-0.12	0.17
Wood	687	-0.10	0.12	-0.19	0.15
Wyandot	288	0.03	0.13	0.08	0.17
Total	50944				

Table A.6: Comparing Diabetes Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.17	0.09	0.20	0.09
Allen	394	0.00	0.10	0.00	0.10
Ashland	323	-0.09	0.10	-0.06	0.11
Ashtabula	403	-0.06	0.10	-0.07	0.10
Athens	336	-0.01	0.10	-0.04	0.11
Auglaize	272	0.02	0.11	0.04	0.11
Belmont	348	0.04	0.10	0.10	0.11
Brown	662	-0.03	0.09	-0.01	0.09
Butler	1284	0.00	0.07	-0.07	0.07
Carroll	303	-0.08	0.11	-0.09	0.11
Champaign	314	-0.07	0.11	-0.07	0.11
Clark	407	0.02	0.10	0.04	0.10
Clermont	1060	-0.02	0.08	-0.07	0.08
Clinton	293	0.21	0.10	0.25	0.11
Columbiana	466	0.07	0.09	0.08	0.10
Coshocton	376	0.08	0.10	0.12	0.10
Crawford	291	-0.05	0.11	0.00	0.11
Cuyahoga	4103	-0.06	0.04	-0.07	0.04
Darke	469	-0.18	0.10	-0.18	0.10
Defiance	337	-0.14	0.11	-0.16	0.11
Delaware	335	-0.16	0.11	-0.26	0.11
Erie	407	-0.04	0.10	-0.04	0.10
Fairfield	288	-0.01	0.11	-0.04	0.11
Fayette	279	0.15	0.10	0.20	0.11
Franklin	3118	0.07	0.05	-0.04	0.05
Fulton	266	0.00	0.11	-0.03	0.12
Gallia	310	0.04	0.10	0.07	0.11
Geauga	262	-0.17	0.11	-0.21	0.12
Greene	350	-0.07	0.10	-0.11	0.11
Guernsey	290	0.01	0.11	0.03	0.11
Hamilton	2266	-0.07	0.06	-0.11	0.06
Hancock	396	0.06	0.10	0.03	0.10
Hardin	280	0.07	0.10	0.13	0.11
Harrison	262	-0.01	0.11	0.03	0.11
Henry	303	-0.07	0.11	-0.09	0.11
Highland	634	0.06	0.09	0.08	0.09
Hocking	269	-0.02	0.11	-0.01	0.11
Holmes	326	-0.06	0.10	-0.06	0.11
Huron	402	0.03	0.10	0.04	0.10
Jackson	307	0.10	0.10	0.17	0.11

Continued on next page

Table A.6 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	0.02	0.10	0.07	0.11
Knox	327	0.02	0.10	0.03	0.11
Lake	377	-0.10	0.10	-0.13	0.11
Lawrence	359	0.18	0.10	0.21	0.10
Licking	286	0.08	0.11	0.00	0.11
Logan	296	0.05	0.11	0.05	0.11
Lorain	1878	-0.08	0.06	-0.09	0.06
Lucas	1857	0.13	0.06	0.11	0.06
Madison	280	0.11	0.10	0.15	0.11
Mahoning	1324	-0.11	0.07	-0.06	0.07
Marion	398	0.06	0.10	0.11	0.10
Medina	251	-0.15	0.11	-0.21	0.12
Meigs	480	0.12	0.09	0.15	0.10
Mercer	329	-0.19	0.11	-0.22	0.11
Miami	332	0.00	0.10	0.03	0.11
Monroe	232	0.00	0.11	0.06	0.12
Montgomery	1770	0.19	0.06	0.20	0.06
Morgan	319	0.16	0.10	0.17	0.11
Morrow	266	0.00	0.11	0.00	0.11
Muskingum	337	0.02	0.10	0.01	0.11
Noble	261	0.05	0.11	0.05	0.11
Ottawa	316	-0.11	0.10	-0.09	0.11
Paulding	320	0.17	0.10	0.19	0.11
Perry	267	0.03	0.11	0.03	0.11
Pickaway	282	-0.01	0.11	-0.03	0.11
Pike	406	0.21	0.10	0.24	0.10
Portage	285	0.00	0.11	-0.03	0.11
Preble	354	-0.03	0.10	-0.03	0.11
Putnam	306	-0.11	0.11	-0.12	0.11
Richland	341	0.00	0.10	0.04	0.11
Ross	365	0.13	0.10	0.11	0.10
Sandusky	398	-0.04	0.10	-0.04	0.10
Scioto	462	0.05	0.09	0.09	0.10
Seneca	361	0.08	0.10	0.09	0.10
Shelby	326	0.01	0.10	-0.02	0.11
Stark	1137	-0.12	0.07	-0.13	0.08
Summit	3346	0.02	0.05	0.02	0.05
Trumbull	617	-0.15	0.09	-0.15	0.09
Tuscarawas	556	0.00	0.09	0.00	0.09
Union	286	0.01	0.11	-0.03	0.11
Van Wert	301	-0.07	0.11	-0.06	0.11

Continued on next page

Table A.6 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.18	0.11	0.23	0.11
Warren	748	-0.15	0.09	-0.25	0.09
Washington	378	-0.09	0.10	-0.05	0.11
Wayne	661	-0.09	0.09	-0.04	0.09
Williams	337	-0.09	0.10	-0.11	0.11
Wood	687	-0.02	0.09	-0.05	0.09
Wyandot	288	-0.08	0.11	-0.08	0.11
Total	50944				

Table A.7: Comparing Cancer Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.06	0.08	0.04	0.07
Allen	394	-0.01	0.08	0.00	0.08
Ashland	323	0.00	0.08	0.03	0.08
Ashtabula	403	0.00	0.08	0.00	0.08
Athens	336	0.07	0.08	0.04	0.08
Auglaize	272	0.00	0.08	0.01	0.08
Belmont	348	0.02	0.08	0.04	0.08
Brown	662	0.03	0.07	0.04	0.07
Butler	1284	0.09	0.06	0.04	0.06
Carroll	303	-0.08	0.08	-0.06	0.08
Champaign	314	-0.01	0.08	0.00	0.08
Clark	407	-0.08	0.08	-0.06	0.08
Clermont	1060	0.12	0.07	0.08	0.06
Clinton	293	-0.03	0.08	-0.02	0.08
Columbiana	466	0.00	0.08	0.00	0.07
Coshocton	376	0.05	0.08	0.06	0.08
Crawford	291	-0.02	0.08	0.01	0.08
Cuyahoga	4103	-0.17	0.05	-0.18	0.04
Darke	469	0.07	0.08	0.07	0.07
Defiance	337	-0.02	0.08	-0.01	0.08
Delaware	335	0.03	0.08	-0.01	0.08
Erie	407	0.00	0.08	0.00	0.08
Fairfield	288	0.04	0.08	0.02	0.08
Fayette	279	0.02	0.08	0.02	0.08
Franklin	3118	0.03	0.05	-0.10	0.05
Fulton	266	0.03	0.09	0.01	0.08
Gallia	310	0.06	0.08	0.06	0.08
Geauga	262	-0.01	0.09	-0.01	0.08
Greene	350	0.05	0.08	0.03	0.08
Guernsey	290	0.01	0.08	0.03	0.08
Hamilton	2266	0.09	0.05	0.05	0.05
Hancock	396	-0.02	0.08	-0.02	0.08
Hardin	280	-0.02	0.08	0.00	0.08
Harrison	262	-0.01	0.08	0.01	0.08
Henry	303	0.00	0.08	0.01	0.08
Highland	634	-0.02	0.08	-0.01	0.07
Hocking	269	0.02	0.08	0.02	0.08
Holmes	326	0.04	0.08	0.04	0.08
Huron	402	0.00	0.08	0.01	0.08
Jackson	307	0.05	0.08	0.06	0.08

Continued on next page

Table A.7 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.07	0.08	-0.05	0.08
Knox	327	0.06	0.08	0.06	0.08
Lake	377	-0.01	0.08	-0.01	0.08
Lawrence	359	0.12	0.08	0.10	0.08
Licking	286	0.05	0.09	0.02	0.08
Logan	296	-0.01	0.08	-0.01	0.08
Lorain	1878	-0.04	0.06	-0.04	0.05
Lucas	1857	-0.09	0.06	-0.13	0.06
Madison	280	0.00	0.08	0.02	0.08
Mahoning	1324	-0.08	0.06	-0.03	0.06
Marion	398	-0.04	0.08	0.00	0.08
Medina	251	0.00	0.09	-0.02	0.08
Meigs	480	-0.04	0.08	-0.03	0.07
Mercer	329	-0.10	0.08	-0.08	0.08
Miami	332	0.06	0.08	0.08	0.08
Monroe	232	-0.03	0.09	0.00	0.08
Montgomery	1770	-0.02	0.06	-0.01	0.06
Morgan	319	-0.06	0.08	-0.06	0.08
Morrow	266	-0.03	0.09	-0.02	0.08
Muskingum	337	0.08	0.08	0.05	0.08
Noble	261	0.01	0.09	0.00	0.08
Ottawa	316	-0.03	0.08	0.01	0.08
Paulding	320	0.02	0.08	0.02	0.08
Perry	267	0.03	0.09	0.02	0.08
Pickaway	282	-0.04	0.08	-0.03	0.08
Pike	406	0.03	0.08	0.01	0.08
Portage	285	0.04	0.08	0.03	0.08
Preble	354	0.07	0.08	0.08	0.08
Putnam	306	-0.11	0.08	-0.10	0.08
Richland	341	0.00	0.08	0.02	0.08
Ross	365	0.00	0.08	-0.01	0.08
Sandusky	398	0.02	0.08	0.01	0.08
Scioto	462	0.01	0.08	0.02	0.07
Seneca	361	0.04	0.08	0.04	0.08
Shelby	326	-0.03	0.08	-0.04	0.08
Stark	1137	-0.02	0.07	-0.02	0.06
Summit	3346	-0.03	0.05	-0.04	0.04
Trumbull	617	0.01	0.08	0.02	0.07
Tuscarawas	556	-0.08	0.08	-0.06	0.07
Union	286	0.01	0.09	-0.01	0.08
Van Wert	301	-0.04	0.08	-0.02	0.08

Continued on next page

Table A.7 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.07	0.09	0.07	0.08
Warren	748	0.02	0.07	-0.03	0.07
Washington	378	0.01	0.08	0.04	0.08
Wayne	661	-0.13	0.07	-0.08	0.07
Williams	337	-0.09	0.08	-0.08	0.08
Wood	687	-0.03	0.07	-0.04	0.07
Wyandot	288	-0.03	0.08	-0.01	0.08
Total	50944				

Table A.8: Comparing Obesity Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	-0.03	0.07	0.00	0.08
Allen	394	-0.01	0.08	-0.03	0.08
Ashland	323	0.07	0.08	0.07	0.09
Ashtabula	403	-0.05	0.08	-0.04	0.08
Athens	336	-0.11	0.08	-0.14	0.09
Auglaize	272	0.07	0.08	0.07	0.09
Belmont	348	-0.01	0.08	0.01	0.09
Brown	662	0.06	0.07	0.08	0.07
Butler	1284	-0.13	0.05	-0.18	0.06
Carroll	303	-0.05	0.08	-0.05	0.09
Champaign	314	0.09	0.08	0.11	0.09
Clark	407	0.06	0.07	0.07	0.08
Clermont	1060	0.00	0.06	-0.01	0.06
Clinton	293	0.00	0.08	0.01	0.09
Columbiana	466	0.02	0.07	0.02	0.08
Coshocton	376	0.01	0.08	0.02	0.08
Crawford	291	0.06	0.08	0.10	0.09
Cuyahoga	4103	-0.11	0.03	-0.11	0.03
Darke	469	-0.03	0.07	-0.05	0.08
Defiance	337	0.02	0.08	0.02	0.09
Delaware	335	-0.17	0.08	-0.24	0.09
Erie	407	0.01	0.08	0.00	0.08
Fairfield	288	0.04	0.08	0.04	0.09
Fayette	279	-0.05	0.08	-0.04	0.09
Franklin	3118	-0.03	0.04	-0.04	0.04
Fulton	266	0.03	0.08	0.02	0.09
Gallia	310	0.01	0.08	0.02	0.09
Geauga	262	-0.11	0.08	-0.16	0.09
Greene	350	-0.08	0.08	-0.11	0.09
Guernsey	290	0.01	0.08	0.02	0.09
Hamilton	2266	-0.12	0.04	-0.15	0.04
Hancock	396	-0.01	0.08	-0.05	0.08
Hardin	280	0.09	0.08	0.11	0.09
Harrison	262	0.06	0.08	0.10	0.09
Henry	303	0.00	0.08	-0.01	0.09
Highland	634	-0.03	0.07	-0.03	0.07
Hocking	269	0.16	0.08	0.22	0.09
Holmes	326	0.05	0.08	0.08	0.09
Huron	402	0.03	0.08	0.04	0.08
Jackson	307	0.06	0.08	0.10	0.09

Continued on next page

Table A.8 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	0.06	0.08	0.09	0.09
Knox	327	-0.08	0.08	-0.11	0.09
Lake	377	-0.13	0.08	-0.16	0.09
Lawrence	359	0.05	0.08	0.10	0.08
Licking	286	0.01	0.08	-0.02	0.09
Logan	296	0.03	0.08	0.04	0.09
Lorain	1878	-0.05	0.05	-0.07	0.05
Lucas	1857	0.14	0.04	0.18	0.05
Madison	280	0.07	0.08	0.09	0.09
Mahoning	1324	-0.11	0.05	-0.10	0.06
Marion	398	0.06	0.08	0.06	0.08
Medina	251	-0.10	0.08	-0.15	0.09
Meigs	480	0.01	0.07	0.03	0.08
Mercer	329	-0.08	0.08	-0.12	0.09
Miami	332	0.03	0.08	0.02	0.09
Monroe	232	0.12	0.08	0.17	0.09
Montgomery	1770	0.02	0.05	0.02	0.05
Morgan	319	0.10	0.08	0.14	0.09
Morrow	266	0.01	0.08	0.02	0.09
Muskingum	337	0.10	0.08	0.14	0.09
Noble	261	0.12	0.08	0.16	0.09
Ottawa	316	0.01	0.08	0.00	0.09
Paulding	320	0.04	0.08	0.04	0.09
Perry	267	0.10	0.08	0.14	0.09
Pickaway	282	0.09	0.08	0.10	0.09
Pike	406	0.03	0.08	0.06	0.08
Portage	285	-0.05	0.08	-0.08	0.09
Preble	354	0.00	0.08	-0.01	0.09
Putnam	306	0.06	0.08	0.07	0.09
Richland	341	-0.05	0.08	-0.07	0.09
Ross	365	0.06	0.08	0.07	0.08
Sandusky	398	0.05	0.08	0.07	0.08
Scioto	462	0.02	0.07	0.05	0.08
Seneca	361	-0.06	0.08	-0.09	0.09
Shelby	326	0.04	0.08	0.04	0.09
Stark	1137	-0.13	0.06	-0.15	0.06
Summit	3346	-0.10	0.04	-0.09	0.04
Trumbull	617	0.04	0.07	0.04	0.07
Tuscarawas	556	-0.07	0.07	-0.07	0.08
Union	286	-0.01	0.08	-0.04	0.09
Van Wert	301	-0.03	0.08	-0.05	0.09

Continued on next page

Table A.8 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.08	0.08	0.12	0.09
Warren	748	-0.14	0.07	-0.21	0.07
Washington	378	0.02	0.08	0.04	0.08
Wayne	661	-0.14	0.07	-0.17	0.07
Williams	337	-0.09	0.08	-0.12	0.09
Wood	687	-0.01	0.07	-0.05	0.07
Wyandot	288	-0.02	0.08	-0.03	0.09
Total	50944				

Table A.9: Comparing Need Rx Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.02	0.10	0.14	0.10
Allen	394	-0.05	0.11	-0.07	0.12
Ashland	323	-0.01	0.11	-0.09	0.13
Ashtabula	403	-0.03	0.10	0.03	0.11
Athens	336	-0.07	0.11	-0.04	0.12
Auglaize	272	0.03	0.12	-0.01	0.13
Belmont	348	-0.07	0.11	-0.03	0.12
Brown	662	0.28	0.09	0.36	0.09
Butler	1284	0.09	0.07	0.02	0.07
Carroll	303	-0.05	0.11	-0.05	0.13
Champaign	314	-0.04	0.11	-0.05	0.13
Clark	407	0.21	0.10	0.22	0.11
Clermont	1060	0.22	0.07	0.21	0.08
Clinton	293	0.09	0.11	0.12	0.12
Columbiana	466	0.11	0.10	0.18	0.11
Coshocton	376	-0.10	0.11	-0.06	0.12
Crawford	291	-0.09	0.11	-0.09	0.13
Cuyahoga	4103	-0.03	0.04	-0.01	0.04
Darke	469	-0.08	0.10	-0.10	0.11
Defiance	337	-0.11	0.11	-0.15	0.13
Delaware	335	0.03	0.11	-0.05	0.12
Erie	407	-0.10	0.11	-0.16	0.12
Fairfield	288	-0.05	0.12	-0.10	0.13
Fayette	279	-0.14	0.12	-0.11	0.13
Franklin	3118	0.16	0.05	0.21	0.05
Fulton	266	-0.12	0.12	-0.17	0.14
Gallia	310	0.22	0.11	0.34	0.12
Geauga	262	0.00	0.12	-0.11	0.13
Greene	350	-0.10	0.11	-0.17	0.13
Guernsey	290	0.04	0.11	0.09	0.12
Hamilton	2266	-0.06	0.06	-0.08	0.06
Hancock	396	-0.02	0.11	-0.07	0.12
Hardin	280	0.09	0.11	0.12	0.13
Harrison	262	0.06	0.11	0.15	0.13
Henry	303	-0.16	0.12	-0.23	0.13
Highland	634	0.12	0.09	0.16	0.09
Hocking	269	0.15	0.11	0.26	0.12
Holmes	326	-0.17	0.11	-0.18	0.13
Huron	402	0.01	0.10	0.04	0.11
Jackson	307	0.17	0.11	0.29	0.12

Continued on next page

Table A.9 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.09	0.11	-0.09	0.12
Knox	327	-0.06	0.11	-0.13	0.13
Lake	377	0.00	0.11	-0.05	0.12
Lawrence	359	0.00	0.11	0.11	0.12
Licking	286	0.01	0.12	-0.02	0.13
Logan	296	-0.14	0.12	-0.18	0.13
Lorain	1878	0.02	0.06	-0.06	0.06
Lucas	1857	0.13	0.06	0.28	0.06
Madison	280	0.05	0.11	0.05	0.13
Mahoning	1324	-0.06	0.07	-0.05	0.07
Marion	398	0.02	0.11	0.00	0.12
Medina	251	-0.06	0.12	-0.14	0.14
Meigs	480	0.12	0.10	0.20	0.10
Mercer	329	-0.26	0.12	-0.35	0.13
Miami	332	-0.08	0.11	-0.14	0.13
Monroe	232	-0.03	0.12	0.00	0.14
Montgomery	1770	0.26	0.06	0.29	0.06
Morgan	319	0.06	0.11	0.18	0.12
Morrow	266	-0.03	0.12	0.01	0.13
Muskingum	337	-0.08	0.11	-0.03	0.12
Noble	261	0.15	0.11	0.25	0.13
Ottawa	316	-0.02	0.11	-0.11	0.13
Paulding	320	0.05	0.11	0.06	0.12
Perry	267	0.01	0.11	0.09	0.13
Pickaway	282	0.00	0.12	-0.02	0.13
Pike	406	0.11	0.10	0.24	0.11
Portage	285	0.01	0.12	-0.02	0.13
Preble	354	-0.10	0.11	-0.15	0.12
Putnam	306	-0.14	0.12	-0.20	0.13
Richland	341	-0.02	0.11	-0.05	0.12
Ross	365	0.11	0.11	0.17	0.11
Sandusky	398	-0.06	0.11	-0.07	0.12
Scioto	462	0.09	0.10	0.19	0.11
Seneca	361	-0.18	0.11	-0.21	0.13
Shelby	326	-0.06	0.11	-0.08	0.13
Stark	1137	0.01	0.08	0.02	0.08
Summit	3346	0.07	0.05	0.11	0.05
Trumbull	617	-0.05	0.09	-0.06	0.10
Tuscarawas	556	-0.10	0.10	-0.05	0.10
Union	286	0.00	0.12	-0.07	0.13
Van Wert	301	-0.08	0.12	-0.16	0.13

Continued on next page

Table A.9 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.28	0.11	0.45	0.12
Warren	748	-0.01	0.09	-0.13	0.10
Washington	378	0.00	0.11	0.02	0.12
Wayne	661	-0.16	0.10	-0.21	0.10
Williams	337	0.02	0.11	-0.01	0.12
Wood	687	0.02	0.09	-0.10	0.10
Wyandot	288	-0.20	0.12	-0.27	0.13
Total	50944				

Table A.10: Comparing No Pay Bills Estimates

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Adams	490	0.10	0.08	0.28	0.09
Allen	394	0.13	0.08	0.16	0.09
Ashland	323	-0.08	0.09	-0.18	0.11
Ashtabula	403	-0.01	0.08	0.06	0.09
Athens	336	-0.04	0.09	-0.01	0.10
Auglaize	272	0.02	0.09	-0.03	0.11
Belmont	348	-0.05	0.09	-0.01	0.10
Brown	662	0.20	0.07	0.29	0.08
Butler	1284	0.07	0.06	-0.01	0.06
Carroll	303	-0.03	0.09	-0.02	0.11
Champaign	314	0.01	0.09	0.00	0.10
Clark	407	0.06	0.08	0.06	0.09
Clermont	1060	0.11	0.06	0.09	0.06
Clinton	293	0.03	0.09	0.03	0.11
Columbiana	466	-0.01	0.08	0.04	0.09
Coshocton	376	-0.09	0.08	-0.04	0.10
Crawford	291	0.00	0.09	0.04	0.11
Cuyahoga	4103	0.06	0.04	0.07	0.04
Darke	469	-0.08	0.08	-0.10	0.09
Defiance	337	-0.06	0.09	-0.10	0.10
Delaware	335	-0.06	0.09	-0.20	0.11
Erie	407	-0.02	0.08	-0.07	0.10
Fairfield	288	-0.01	0.09	-0.05	0.11
Fayette	279	-0.04	0.09	0.02	0.11
Franklin	3118	0.13	0.04	0.18	0.04
Fulton	266	0.00	0.09	-0.02	0.11
Gallia	310	0.05	0.09	0.14	0.10
Geauga	262	-0.08	0.09	-0.25	0.11
Greene	350	-0.17	0.09	-0.32	0.11
Guernsey	290	0.04	0.09	0.11	0.10
Hamilton	2266	-0.08	0.05	-0.12	0.05
Hancock	396	0.00	0.09	-0.06	0.10
Hardin	280	0.02	0.09	0.04	0.11
Harrison	262	0.01	0.09	0.11	0.11
Henry	303	-0.08	0.09	-0.15	0.11
Highland	634	0.13	0.07	0.20	0.08
Hocking	269	0.07	0.09	0.17	0.11
Holmes	326	-0.11	0.09	-0.09	0.10
Huron	402	0.01	0.08	0.05	0.10
Jackson	307	0.00	0.09	0.08	0.10

Continued on next page

Table A.10 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Jefferson	338	-0.08	0.09	-0.11	0.10
Knox	327	0.06	0.09	0.02	0.10
Lake	377	0.05	0.09	0.01	0.10
Lawrence	359	0.08	0.08	0.24	0.10
Licking	286	-0.06	0.09	-0.13	0.11
Logan	296	-0.01	0.09	-0.02	0.11
Lorain	1878	0.04	0.05	-0.06	0.05
Lucas	1857	0.20	0.05	0.36	0.05
Madison	280	0.11	0.09	0.12	0.11
Mahoning	1324	-0.12	0.06	-0.12	0.06
Marion	398	0.00	0.09	-0.06	0.10
Medina	251	-0.13	0.09	-0.27	0.12
Meigs	480	0.03	0.08	0.13	0.09
Mercer	329	-0.09	0.09	-0.15	0.11
Miami	332	-0.01	0.09	-0.08	0.10
Monroe	232	-0.13	0.09	-0.15	0.12
Montgomery	1770	0.08	0.05	0.10	0.05
Morgan	319	-0.02	0.09	0.09	0.10
Morrow	266	-0.08	0.09	-0.06	0.11
Muskingum	337	-0.02	0.09	0.04	0.10
Noble	261	0.10	0.09	0.23	0.11
Ottawa	316	-0.04	0.09	-0.16	0.11
Paulding	320	0.02	0.09	0.01	0.10
Perry	267	-0.07	0.09	0.00	0.11
Pickaway	282	-0.02	0.09	-0.04	0.11
Pike	406	0.04	0.08	0.19	0.09
Portage	285	0.08	0.09	0.05	0.11
Preble	354	-0.01	0.09	-0.03	0.10
Putnam	306	-0.10	0.09	-0.17	0.11
Richland	341	0.03	0.09	0.00	0.10
Ross	365	0.03	0.08	0.09	0.10
Sandusky	398	0.00	0.08	0.01	0.10
Scioto	462	0.11	0.08	0.22	0.09
Seneca	361	-0.05	0.09	-0.07	0.10
Shelby	326	-0.06	0.09	-0.09	0.10
Stark	1137	-0.02	0.06	-0.01	0.06
Summit	3346	0.02	0.04	0.05	0.04
Trumbull	617	0.10	0.07	0.12	0.08
Tuscarawas	556	0.01	0.08	0.08	0.08
Union	286	0.02	0.09	-0.04	0.11
Van Wert	301	-0.07	0.09	-0.16	0.11

Continued on next page

Table A.10 – continued from previous page

		Conditional Model *gllamm*		Unconditional Model *xtmixed*	
County	N	Estimate	SE	Estimate	SE
Vinton	235	0.14	0.09	0.33	0.11
Warren	748	-0.08	0.07	-0.25	0.08
Washington	378	-0.03	0.09	-0.02	0.10
Wayne	661	-0.18	0.08	-0.27	0.08
Williams	337	0.08	0.09	0.07	0.10
Wood	687	-0.04	0.08	-0.19	0.08
Wyandot	288	-0.07	0.09	-0.12	0.11
Total	50944				

Stata Code

```
/* Calculating Statewide Prevalence Rates for Each Category */
svy: proportion var, over(agecategory)
estat effects

/*Calculating Total Population 18+*/
bys county_a: gen total = (Male1824 + Male2534 + Male3544 + Male4554 ///
+ Male5564 + Male65plus + Female1824 + Female2534 + Female3544 ///
+ Female4554 + Female5564 + Female65plus)
la var total "Total Adult (18+) Population"
save, replace

/*Computing the Synthetic Estimates */
/*Step One: Calculate Ratio by Total Population */
/*Note: 'total' indicates total population from census data. */
bys county_a: gen ratio_1 = Male1824/total
bys county_a: gen ratio_2 = Male2534/total
bys county_a: gen ratio_3 = Male3544/total
bys county_a: gen ratio_4 = Male4554/total
bys county_a: gen ratio_5 = Male5564/total
bys county_a: gen ratio_6 = Male65plus/total
bys county_a: gen ratio_7 = Female1824/total
bys county_a: gen ratio_8 = Female2534/total
bys county_a: gen ratio_9 = Female3544/total
bys county_a: gen ratio_10 = Female4554/total
bys county_a: gen ratio_11 = Female5564/total
bys county_a: gen ratio_12 = Female65plus/total

/*Step Two: Create ratio variable. */
/*Note: The values were generated by Step One. */
bys county_a: gen varp_dotj1 = 0.01045
bys county_a: gen varp_dotj2 = 0.0277728
bys county_a: gen varp_dotj3 = 0.0585747
bys county_a: gen varp_dotj4 = 0.1013919
bys county_a: gen varp_dotj5 = 0.1913217
bys county_a: gen varp_dotj6 = 0.2581227
bys county_a: gen varp_dotj7 = 0.0351516
bys county_a: gen varp_dotj8 = 0.0599244
bys county_a: gen varp_dotj9 = 0.0784357
bys county_a: gen varp_dotj10 = 0.1022843
bys county_a: gen varp_dotj11 = 0.177564
bys county_a: gen varp_dotj12 = 0.225574

/*Step Three: Generate synthetic estimate for each group. */
bys county_a: gen varsynth_est_1 = ratio_1 * (varp_dotj1 *100)
bys county_a: gen varsynth_est_2 = ratio_2 * (varp_dotj2 *100)
bys county_a: gen varsynth_est_3 = ratio_3 * (varp_dotj3 *100)
```

```
bys county_a: gen varsynth_est_4 = ratio_4 * (varp_dotj4 *100)
bys county_a: gen varsynth_est_5 = ratio_5 * (varp_dotj5 *100)
bys county_a: gen varsynth_est_6 = ratio_6 * (varp_dotj6 *100)
bys county_a: gen varsynth_est_7 = ratio_7 * (varp_dotj7 *100)
bys county_a: gen varsynth_est_8 = ratio_8 * (varp_dotj8 *100)
bys county_a: gen varsynth_est_9 = ratio_9 * (varp_dotj9 *100)
bys county_a: gen varsynth_est_10 = ratio_10 * (varp_dotj10 *100)
bys county_a: gen varsynth_est_11 = ratio_11 * (varp_dotj11 *100)
bys county_a: gen varsynth_est_12 = ratio_12 * (varp_dotj12 *100)

/*Step Four: Aggregate estimates for each group. */
bys county_a: gen varsynthetic_estimate = (varsynth_est_1 + varsynth_est_2 ///
+ varsynth_est_3 + varsynth_est_4 + varsynth_est_5 + ///
varsynth_est_6 + varsynth_est_7 + varsynth_est_8 ///
+ varsynth_est_9 + varsynth_est_10 + varsynth_est_11 ///
+ varsynth_est_12)

/* Estimates using gllamm */
/* For complete documentation see: http://bepress.com/ucbbiostat/paper160 */
/* Installing gllamm */
ssc describe gllamm
ssc install gllamm

/* Running gllamm */
gllamm depvar, i(county_a) link(logit) family(binom) adapt trace
gllamm, eform
gllapred zeta1, u /*The posterior mean and sd of the latent variable */
gllapred mu1, mu /*The predicted probability of the response variable */
gllapred y1, xb /*The fixed-effects part of the linear predictor */
gllapred var1, ustd /*Standardized posterior means of the residuals */

/* Mixed-Effects Logit Models */
/* Fitting Random Intercepts for County */
xtmelogit hibloodpres ///
|| county_a: , intpoints(30)
predict b*, reffects level(county_a)
predict se*, reses level(county_a)
predict P1
predict P2, fixedonly
predict hbpoffset, xb
est store hbpNoInt
```