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draft completed July 4, 2012

Mixing AutoMetrics with MARS: A study of psychological sequelae of Chornobyl

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OxMetrics Users Group Conference
Cass Business school
London City University,
106 Bunhill Row
London, U.K.

3-4 September 2012

Contents

1 Acknowledgements

This project has been funded by National Science Foundation HSD grant 08262983, and to them we remain deeply grateful. We would also like to thank the Ministry of Health in the Ukraine for their cooperation in this study. We are grateful to the developers of Stata in College Station, Texas, Salford Systems, Inc. in San

Diego, California, and AutoMetrics in Oxford, London for the software they have developed and which we are using.

2 Introduction

The current study conducted a random population sampling of Ukrainian residents in the Kiev and Zhytomir oblasts of that country, with the aim of developing long-term models of human nuclear disaster risk. Living in relatively close proximity to the Chornobyl Nuclear station in Ukraine, these residents were exposed to the largest industrial radiological accident to date in 1986. A survey methodology was used to assess the complex bio-psycho-social pathways that contribute to long-term population outcomes after a significant radiological event. Data collection was conducted from 2008-2011. The project was funded by the National Science Foundation, Division of Decision, Risk and Uncertainty (082-6983); and conducted in cooperation with the Ministry of Health of Ukraine. In the effort to understand the long-term burden of nuclear accident exposure on a general population, investigators primary foci of interest included: the populations reconstructed cumulative dose exposure to ^{137} Caesium (radiation source term for the Chornobyl event), cognitive perception of risk to health and environment, mental health status (standardized instruments), medical diagnoses (ICD-9), psychosocial functioning, health behavior, reproductive patterns, nutritional practices, Chornobyl accident information sources, and social communication networks. These domains were assessed in the population for their current status, and retrospectively for three earlier time periods from 1986 to the time of the survey interview. The current presentation describes preliminary statistical exploration of covariates influencing: 1) health-related behaviors as measured by the Nottingham Health Profile, 2) general mental health dysfunction as measured by the Brief Symptom Inventory , and 3) Chornobyl-related post traumatic stress syndrome as measured by the Revised Civilian PTSD Scale.

Research of protracted, low dose radiation exposures from nuclear plant accidents, show relatively low impacts on population health risk [20]. Conversely, population perceptions of risk from radiological events remain active up to several years post-event [1, 3, 5, 12]. Toxic accidents (radiological, chemical, biologic agents) appear to drive a unique spectrum of psychosocial and behavioral responses in affected populations. These responses are distinct from event-related physical injury. They include depression, anxiety, traumatic response, increased medical services utilization, phobic nutritional behavior and changes in reproductive patterns [2, 3, 5, 6, 7].

3 Data collection and sampling

A sampling of 703 participants was conducted by means of a probability household sample of the Kiev and Zhytomir oblasts (states) of Ukraine to insure representativeness. Random phone number generation of each area code was conducted. Informed and consenting respondents were then visited by trained interviewers who administered the Research Survey Questionnaire in an interview format. Responses were entered in interviewers hand-held computers, then uploaded for storage to a website constructed for the study (Vovici Corporation, USA). Participants ranged in age from 28-84.

4 Research instruments and measures

The study investigated a comprehensive set of factors (predictor factors) established in previous radiological and technological accident research to impact on health, mental health, psychosocial behavior and health behavior (outcome factors). All factors were queried by means of survey questions and psychometric scales collated into the Research Survey Questionnaire, and administered in native language by local interviewers.

4.0.1 Predictor Factors

These included demographics, perception of radiation risk and nuclear attitudes, Chornobyl cognitions [1, 8], Chornobyl information sources, accident characteristics (distance, relocation, etc.), general hazards perception, negative life events and buffers, coping style (Coping Strategy Indicator) [7]. Finally, radiation dose exposure to ^{137}Caesium was estimated for each participant (see below)

4.0.2 Outcome Factor Measures

Measures of Physical Health: a) ICD-9 Medical Diagnosis. Diagnostic information from the Ukraine Ministry of Health database of annual standardized dispensary exams. b) Nottingham Health Profile. Standardized scale of self-reported health and its impact on multi-domain behavioral functioning [9]. Reliability/validity on Russian language form tested in pilot study [10]. Measures of Mental Health: a) Brief Symptom Inventory [11] Standardized scale measuring patterns of psychological distress: depression, anxiety, somatization, obsessive-compulsiveness, hostility, paranoia, psychoticism , global distress, positive symptom score. Russian form pilot tested [10]. b) Revised Civilian PTSD Scale. Russian version anchored in Chornobyl event and restandardized [12]. Measures general post traumatic stress and distress clusters related to Chornobyl. Reliabilities tested on pilot study of current sample [10]. of Psychosocial/Health Behavior: These factors have been associated with toxic accident behavioral outcomes and are integrated within the Research Survey Questionnaire. They include medical services utilization, phobic behavior, substance use, eating habits, abortions and contraceptive use.

5 Objectives

Our prinicpal objective is to explore the study of the psychological sequelae of the Chornobyl disaster with respect to its effect on the part Ukrainian residents in the area. But in this paper it is to determine what MARS contributes our analysis when we pipe its output into AutoMetrics with respect to a preliminary assessment of the extent to which there is an empirical dose - mental health effect to be explored.

We hope to answer two fundamental questions concerning the value added to our analysis by MARS. Does MARS help us explore dimensions of our data which we might have ignored? The other question is: Does MARS aid in providing a well-behaved model for our investigation of the subject of choice?

Our objective was to include as many of the essential covariates in our analysis as we could to minimize omitted variable bias or specification error. We wanted help with variable selection to increase the probability that our analysis was not dominated or substantially plagued by this pernicious form of error. To do so, we wanted to find a method which could be used at the front end of a regression modeling application to assure ourselves that we had construct validity in our model. To have construct validity in the model, we will have captured all of the relevant dimensions of the analysis in the definition of our domain. We know that reality is not linear, so that these dimensions may have entailed nonlinear aspects of reality that our linear regression analysis would not encompass. To merely performing a principle components or factor analysis was not a means of assurance of that construct validity. We had to use a method that would discover what nonlinear aspects would enhance our goodness of fit.

To do so, we decided to use MARS to take advantage of its systematic way of finding non-linear aspects of the analysis that our own criteria for variable inclusion may have missed. In this article we demonstrate how this is done and how it has worked for us in the testing of two of our hypotheses. We find that the application of MARS may provide an invaluable instrument by which to enhance the richness of our findings and help us improve the fit of our data with an application of regression splines.

We also explain why AutoMetrics is needed to optimize the fulfillment of the statistical congruency requirement once we have selected the proper variables.

6 Basic nomenclature

This is a longitudinal study. We examine the subject matter in three waves over time. The first time period or wave covers from the day of the Chornobyl accident, April 26, 1986 to the end of that same year. The second wave extends from January 1, 1987 through December 31, of 1996. The third wave begins in January 1, 1997 and extends to the time of the interview in 2009- 2011, whereas dose reconstruction extends from the date of the accident to the end of 2009.

We reconstruct effective dose, E, from external radiation exposure from radioactivity deposited on the ground, as follows: 1) We determine the dose rate

$D_r(t)$ in air for the isotope, i, as a function of time at 1m above the contaminated surface in the region R. 2) We apply an age dependent fact that converts air into effective whole body dose to the individual, K_j. 3) We include modifying factors that include fraction of time spent outdoors, $f_{a,o}$, and attenuation factors L_H associated with occupancy f_H in buildings and dwellings, so that

$$E = \sum_i \sum_R f_R \sum_o f_0 \sum_H f_H L_H K_{a,i} \int D_{R,i}(t) \tag{1}$$

There are extensive refinements to this formula. For example, Andre Bouville of the National Cancer Institute has refined this model in 2007 for application to thyroid conditions resulting from exposure to ^{131}I from cow's milk by children **??**.

We include in our variable list basis function generated by the program called MARS, referring to multivariate adaptive regression splines, developed by Professor Jerry Friedman [14]. The regression splines have variable names that begin with bf, which stands for the term, basis function. These splines help us analyze the data when it needs to be re-centered or transformed in such a manner that a regression model will find it more linear than it was in its original form.

6.1 A short history of MARS

MARS is a program that generates basis functions (regression splines) that provide a reasonable approximation of a nonlinear function, f(x) over some domain x. It does so without knowing in advance where the knots (sudden turning points) in the function might be. MARS is therefore a flexible nonparametric system that allows us to model a nonlinear process with a linear method.

In the history of automatic modeling, MARS succeeds earlier attempts such as automatic interaction detection (AID) developed by Morgan and Sonquist in the early 1960s [17, 864]. AID was an attempt to accomplish automatic interaction identification and estimation. Interactions are departures from purely additive linear models in that they incorporate joint effects over and above the individual main effects.

6.2 How MARS works

MARs automates variable selection. It transforms variables into truncated regression splines to accommodate nonlinear functional forms. It checks for potential interactions with predictors. It drops irrelevant variables to minimize overfitting [21, 2].

MARS models nonlinear components with a variation of piecewise spline regression models. It uses a recursive partitioning algorithm for the regression problem, which emerged in a program for classification and regression trees, dubbed CART (Brieman, L., Friedman, J., Olshen, R. and Stone, C., 1984).

Originally MARS recursively partitioned the domain into disjoint subregions, within each of which it split the domain into two left and right offspring regions. The regression components would reside either within the left or the right daughter domain. Basis functions have the general form of

$$f(x) = \beta_0 + \sum_{j=1}^{S} h(m)B(m) \tag{2}$$

where $B(x) = I(x \in R_j)$ with I being an indictor function with a value of 1 if x is a condition is true or 0, otherwise. The indicator function then becomes part of a product of a series of step functions, in turn indicating membership of the subregion, formulated as

$$\begin{aligned} H[\eta] &= 1, if\ \eta \geq 0, \\ &= 0,\ otherwise. \end{aligned} \tag{3}$$

such that they could be incorporated as follows [17]

$$B_5(x) = H[x_1 - 0] * H[1 - x_2] * H[x_2 - 0] * H[1 - x_1], \tag{4}$$

which would delineate region 5 as a unit square within the larger region R. But as Stevens and Lewis point out these functions were step functions in disjointed areas. The disjoint requirement precluded MARS from finding linear additive models. Friedman replaced the univariate step functions with truncated regression splines, formulated in pairs, consisting of a primary basis function and a mirror image of it as

$$C = \{(X_j - t)_+, (t - X_j)_+\} \tag{5}$$

where t = represented the knots in the regression splines. The plus indicates that only the positive portion is used. Often, these functions entail recentering the variable around a knot.

The basis function generation follows a stepwise algorithm. MARS begins with a constant and then searches each variable, and for each variable, tests all possible knots. The variable-knot combination that reduces the sum of squared errors the most or increases the sum of squared errors the least is selected. The basis functions generally appear to be hockey-stick transformation. For each primary transformation a mirror image is generated as well. For example if variable x is to be transformed, the basis function transformation might be max(0, 30 - x) and its mirror image would be max (0, x - 30).

Variables that have delayed responses or threshold conditions until a response appears may be approximated by these hockey stick transformations. Many variables in reality have such a nonlinear shape. One example can be seen in the relationship between PTSD and anxiety shown in the left panel Figure 6, where a nonlinear variable is linearized by a basis function transformation.

The transformation that improves the model the most is added to the constant. The model now consists of a constant and a basis function. To see how a basis function renders a relationship more amenable to regression analysis, the reader should refer to Figure 6. It can take a relationship which is essentially nonlinear and convert it to a more linearized function that is more amenable to OLS linear regression modeling. The process repeats itself, each time improving the model it has constructed the most.

The algorithm tests all possible knots on all possible variables by brute force. The knot-variable combination that reduces the sum of squares the most is selected.

The resulting linear combination of basis functions is then used in lieu of a nonlinear regression analysis. These functions are added to the linear combination of basis functions that constitutes the MARS model. For example, when PTSD in wave three is run against average cumulative reconstructed external dose of the respondent to ^{137}CS for women in Figure 1 or men in Figure 2, we can observe that the relationships are nonlinear.

MARS generates sets of pairs of truncated spline transformations for each possible position on the domain of the regressor.They are generated in reflected pairs, always representing the positive part of the domain. These plots often appear as hockey sticks of various dimensions. But just as our patterns of male PTSD against cumulative external dose of ^{137}Cesium reveal piecewise patterns, these hockey stick transformations can serve to linearize delayed, latent, or threshold responses to exogenous variables. For these reasons, relationships that have such a shape may be linearized by MARS and made more amenable to linear OLS regression analysis than otherwise might be the case. Because this is the first empirical examination of this subject, we are partly in an exploratory mode. Therefore, we want to be sure that we explore as many aspects of the relationships that might exist that we can. In situations such as these MARS may provide an invaluable investigative tool to plumb the depths of relationships that could exist within our dataset.

After generating many of these regression splines from the radial basis functions, the pair that diminished the sum of squared errors the most was the pair that was incorporated into the model.[15, 287].

To guard against overfitting by the forward stepwise algorithm, backward pruning was also incorporated into the system, while the model undergoes a 10-fold cross-validation test. Alternatively, the user may opt for a testing segment to be reserved, and then a training segment to preclude that overfitting.

The nonparametric selection of basis function provided a different driver for the model building process that could be modulated at a later stage. It is that last stage where AutoMetrics is brought into the process.

7 Research problem

7.1 Can reconstructed effective radiation dose of ^{137}CS explain psychological health?

We are interested in explaining the relationship between perceived risk of radiation exposure as measured by the self-perceived risk of Chornobyl related-health threats to oneself. The half-life of Cesium 137 is 30.17 years, according to the U.S. environmental protection administration.

We are not relieving ourselves of the responsibility of finding the proper general unrestricted model (GUM). Rather by using MARS, we are finding relationships and interactions that we might not have thought of before while building the model.

MARS will generate the formula for the basis functions which can then be added to the dataset. The inclusion of these basis functions will suggest transformations not suspected of as having been needed. If we do not think that the MARS model has optimized the fit we may attempt a different combination of the generated basis functions. In this way, MARS will have served a heuristic purpose in suggesting variables that are amenable to transformation in some way as to improve the model fit.

One of our statistical objectives is to minimize any kind of specification error we can by including all of the potentially related variables and forming a general unrestricted model from the pool of candidate variables. Whereas AutoMetrics assumes you will select the proper variables, we rely on MARS to provide us with guidance in case we have not thought about the relationship with a particular variable [13, 25-26].

We do think through our choice of candidate variables but wish to be sure that we have not missed an important one. That is where MARS comes into play.

It will generate basis functions from truncated regression splines that appear to be related to the dependent variable. We rely on MARS for help in this connection. Thus, we enhance our chances of not omitting an important variable.

We add covariates that could provide alternative plausible explanations to the relationship we are testing to control for their effects [13, 25-26].

Among the variables we employ as confounders are the socio-demographic characteristics of the respondents, the computed geodesic distance in miles from the accident site, as well as local measures of support that the respondents might experience. As for the sociodemographic characteristics we employ martial status, the number of children for women, and income sufficiency for various levels of quality of life. We also control for perception of risk to oneself of the Chornobyl related health threat in addition to some function of the distance of the respondent at the time of the accident from Chornobyl.

8 Methods

We began our analysis sometimes with as many as 200 variables in the pool of candidate variables in the model. Some of these were more correlated than we would like so we used a minute ($p = .0001$) level to guard against a false discovery rate for our statistical analysis.

It is helpful to know that the ^{137} CS in the Ukraine was not in general very large. Natural background radiation is about 2.4 mSv/year. Depending upon where people were and what they ate, and the extent to which they were outdoors, the amount of radiation to which they were exposed may well have been below the level of normal biological reactivity.

However, that was not always the case. Infant children under the age of 2-5, when their thyroids absorb more iodine from the air, were more affected than older youth whose physical growth had slowed down. When natural iodine uptake from the air had considerably subsided on the part of the youth of five or older, as it does in the natural life cycle, the danger subsided. Moreover, the farther away they were from the accident site, the less their health was threatened, unless the winds shifted direction and carried the radioactive plume to them. For some time, there was considerable uncertainty as to who and how much the health of some people were threatened. In the Ukraine the in area we sampled, the situation can be described by Figure 1.

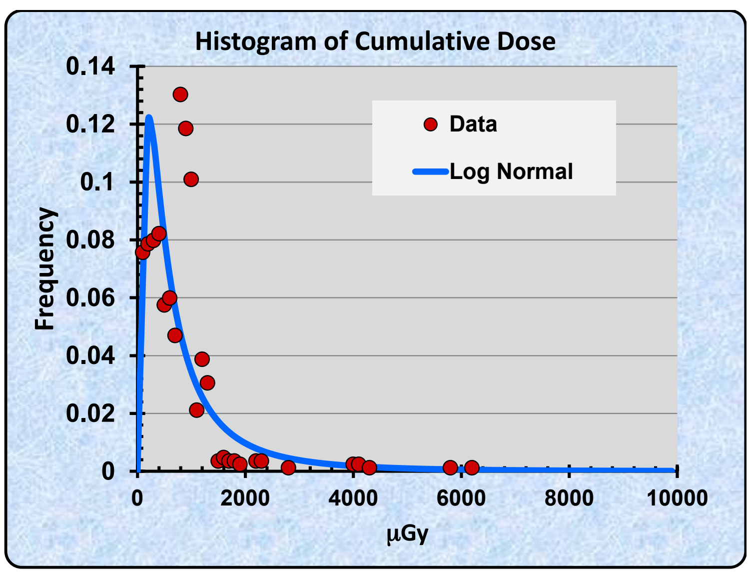

Figure 1: Cumulative ^{137}CS dose in the Ukraine in microGrays

Because our sample was a random one, many of our respondents lived beyond the reach of the exclusion zone, an area of approximately 30 km from Chornobyl. Consequently, the mean effective dose sustained by this sample may not reflect

Table 1: **Deposition of ^{137}CS**

Measure of ^{137}CS	μGrays
minimum:	44
maximum:	26,600
mode:	800
median:	715
mean:	838
standard deviation:	1695
geometric mean:	550
geometric standard deviation:	2.4

the condition of those who were seriously and substantially exposed.

We hope to test this hypothesis with the best possible regression model. What does that mean? We have to have the optimal covariates in the model to assure that the general unrestricted model (GUM) is congruent. We wish to minimize the possibility of specification error by increasing the chance of including relevant covariates in our model. We use MARS to point out potential relationships that we might have missed by automatically and systematically finding relationships in the data by recentering and transforming our variables.

8.1 Assessing the application of regression splines

The world is not linear even if OLS regression wants to treat it as such. Regression splines however can provide a fit of a nonlinear sort that will fulfill many requirements of OLS regression. Peicewise linear regression is an application of a regression spline. It is another way of accommodating a structural break within a period. By setting up separate dummy variables to accommodate these periods within which different regression slopes and intercepts are at work, the model accommodates structural breaks.

9 Findings

9.1 Models for Mental health dysfunctionality

We illustrate this application with a test of two of our hypotheses. Our fourth hypothesis is that cumulative radiation dose of ^{137}CS explains mental health as measured by the Brief Symptom inventory and in this case we use the positive symptom subscale to measure general health dysfunction.

If we examine the relationship between this general mental health dysfunctionality score and the cumulative external dose of ^{137}CS we obtain the patterns revealed by the lowess plots in Figure 2, careful inspection of which will reveal particular nonlinearity. How we can capture this nonlinearity without sacrificing fit is a matter we will deal with having MARS generate the regression splines that will provide the best model fit.

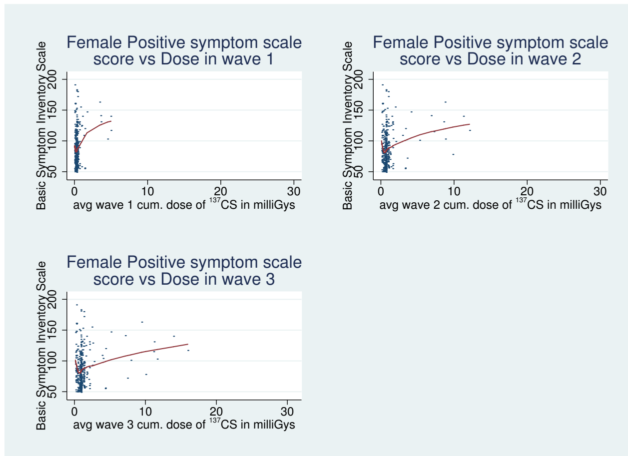

Figure 2: **BSI positive symptom subscale female scores by cumulative ^{137} CS dose over three waves**

We use the covariates of socio-demographic status, the number of medically diagnosed illnesses on the part of the respondent, self-perceived Chornobyl health threat to oneself and one's family, belief in the amount of pollution due to Chornobyl and the basis for the cancer rate in their area of residence, as well as the self-reported depression and anxieties on the previous waves of the study to control for potentially confounding influences. However, we allow MARS to search for other perhaps nonlinear relationships and to construct basis functions which we can include in our analysis. We insert those into the general unrestricted model to be used by AutoMetrics. What happens when we add these basis functions? Basis functions dominate the output. The R^2 rise from 0.365 to 0.941. The number of assumptions violated goes from one to all. We begin with the women.

9.1.1 Female Positive symptom models

In the model below, we use only our normal variables. As we will see, both models provide consistent evidence with regard to our hypothesis that radiation dose explains general mental health as measured by the Brief Symptom Inventory. Both models show that the data are inconsistent with the hypothesis that cumulative dose as reconstructed leads to a decline in mental health. We first build a model, presented in Table 2, to explain mental health on the part of the women in our study.

Table 2 Modelling BSIposymp by OLS-CS
The dataset is: gals.in7
The estimation sample is: 1 - 363
Dropped 3 observation(s) with missing values from the sample

		Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
Constant		36.1449	7.460	6.939	5.21	0.0000	0.0741
age		0.567945	0.1656	0.1737	3.27	0.0012	0.0306
edu3		8.27144	2.726	3.183	2.60	0.0098	0.0195
edu4		-1.86104	5.139	4.521	-0.412	0.6809	0.0005
marrw13		3.87829	3.807	4.073	0.952	0.3416	0.0027
marrw16		-4.68635	11.63	7.866	-0.596	0.5517	0.0010
marrw24		32.7286	23.94	6.326	5.17	0.0000	0.0732
childw1		-2.08219	2.009	2.003	-1.04	0.2993	0.0032
emplw16		10.1987	3.583	3.277	3.11	0.0020	0.0278
emplw23		2.59385	4.633	4.253	0.610	0.5423	0.0011
emplw24		2.61391	24.74	7.494	0.349	0.7275	0.0004
depagw2		0.237815	0.07052	0.06819	3.49	0.0006	0.0346
anxagw1		0.146863	0.03891	0.04042	3.63	0.0003	0.0375
radfmw1		0.0553968	0.08792	0.07394	0.749	0.4542	0.0017
radhlw1		-0.180692	0.09119	0.08640	-2.09	0.0372	0.0127
radhlw3		0.234851	0.04998	0.05035	4.66	0.0000	0.0603
inc4w1		9.02537	5.808	6.853	1.32	0.1887	0.0051
inc1w3		10.2430	3.593	4.756	2.15	0.0320	0.0135
avgcumdosew1	U	4.72494	4.655	4.306	1.10	0.2733	0.0035
avgcumdosew2	U	4.50510	5.896	5.738	0.785	0.4329	0.0018
avgcumdosew3	U	-3.55804	4.255	3.947	-0.901	0.3680	0.0024

sigma	23.0765	RSS	180526.366
R^2	0.365256	F(20,339) =	9.754 [0.000]**
Adj.R^2	0.327808	log-likelihood	-1629.97
no. of observations	360	no. of parameters	21
mean(BSIposymp)	86.6667	se(BSIposymp)	28.1465
When the log-likelihood constant is NOT included:			
AIC	6.33419	SC	6.56088
HQ	6.42433	FPE	563.590
When the log-likelihood constant is included:			
AIC	9.17207	SC	9.39876
HQ	9.26221	FPE	9625.82

Normality test:	Chi^2(2) =	58.204	[0.0000]**
Hetero test:	F(28,329) =	1.1833	[0.2433]
Hetero-X test:	F(73,284) =	0.87766	[0.7442]
RESET23 test:	F(2,337) =	1.9412	[0.1451]

A positive symptom score on the part of the women shows that age, having a technical degree (educ3) and not having graduated college(educ4) are all significantly related.

Marital status apparently is not statistically significant unless one is separated during wave two, the time of economic problems, in which case this appears to be important. Being unemployed(emplw16) is statistically significant, but part time (emplw23) and voluntary work (emplw24) during wave two is not. Income insufficiency during wave (inc1w3) three is also related to this state of mind.

However, self-reported depression (depagw2) and anxiety (anxagw1) in waves two and one, respectively, are statistically associated with general mental dysfunction.

But reconstructed cumulative external dose is not apparently significantly related to general mental health dysfunctionality during any wave (avgcumdosew1 through avgcumdosew3).

Self-perceived Chornobyl related health threat to oneself during waves one (radhlw1) and three (radhlw3) are also statistically related to this mental health dysfunctionality for female respondents.

AutoMetrics has retained the proper covariates from the pool that we have entered into the model. In this model we observe with considerable statistical congruency that are model does no support this hypothesis for women in our study. We then enter into the model the basis functions generated for our female analysis by MARS. The pattern of variables selected for our final model changes. The basis functions now dominate the variable selection process. The model remains consistent with the previous model in that the findings do not support the hypothesis of a dose mental health relationship when using the measure of general mental health functionality of the brief symptom inventory.

```
Table 3 Modelling BSIposymp by OLS-CS
       The dataset is: gals.dta
       The estimation sample is: 1 - 363

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
BFps2f                1.77871     0.1518     0.2158     8.24  0.0000   0.1629
BFps3f                3.64609    0.07497    0.09200     39.6  0.0000   0.8182
BFps3                -3.44030     0.1022     0.1302    -26.4  0.0000   0.6667
BFps4                 3.53564    0.07835     0.1000     35.3  0.0000   0.7816
BFps8w2             -0.638613     0.1687     0.1754    -3.64  0.0003   0.0366
BFps9                -1.70877    0.09559     0.1195    -14.3  0.0000   0.3692
BFps10                2.40125     0.1976     0.2177     11.0  0.0000   0.2585
BFps11               -1.96492     0.1354     0.1634    -12.0  0.0000   0.2930
BFps12               0.155755    0.04992    0.06037     2.58  0.0103   0.0187
BFps22aw1           -0.346626     0.2059     0.1572    -2.20  0.0281   0.0137
BFps28w2             -4.59650      2.512      1.921    -2.39  0.0173   0.0161
avgcumdosew1  U      0.188333      1.400      1.189    0.158  0.8742   0.0001
avgcumdosew2  U       1.86420      1.758      1.550     1.20  0.2300   0.0041
avgcumdosew3  U      -1.23718      1.263      1.287   -0.961  0.3371   0.0026

sigma                 6.94119  RSS                  16814.877
R^2                  0.941297  F(13,349) =    430.5 [0.000]**
Adj.R^2              0.939111  log-likelihood        -1211.24
no. of observations       363  no. of parameters           14
mean(BSIposymp)       86.5069  se(BSIposymp)          28.1296
When the log-likelihood constant is NOT included:
AIC                   3.91275  SC                     4.06295
HQ                    3.97245  FPE                    50.0384
When the log-likelihood constant is included:
AIC                   6.75063  SC                     6.90083
HQ                    6.81033  FPE                    854.628B

// basis function legend
//----------------------
// 1 BFps2f = max(0, phobanx - 2.03628e-00*)
// 2 BFps3f = max(0, WHPer + 3.14933e-007)
// 3 BFps3 = max(0, WHPer - 33.7)
// 4 BFps4 = max(0, 33.7 - WHPer)
// 5 BFps8w2 = max(0, 5 - depagw2)
// 6 BFps9 = max(0,
// 7 BFps10= max(0, BSIpsyc - 4)
// 8 BFps11 = max(0, 17- BSIpar)
// 9 BFps12 = max(0, MiPTSD-44)
// 10 BFps22aw1= max(0, 3-pillw1)
// 11 BFps28w2 = max(0, sepaw2 + 5.41039e-010)

Normality test:   Chi^2(2)  =   18.105 [0.0001]**
Hetero test:      F(25,337) =   1.8159 [0.0108]*
Hetero-X test:    F(97,265) =   2.0224 [0.0000]**
RESET23 test:     F(2,347)  =   1.5619 [0.2112]
```

In Tables two and three, the model output reveals that the regression coefficients for average cumulative reconstructed dose of ^{137}CS remain not significant at the 0.05 level with respect to the BSI positive symptom subscale. In the second model, the basis functions generated by MARS dominate the output insofar as they now constitute 100% of the significant effects. Although the R^2 increases from 0.365 to 0.941, the number of assumptions being violated by the model increases from one to three, leading one to suspect that the MARS program pays no attention to fulfillment of model assumptions in order to maintain statistical congruency.

The use of MARS may improve the fit, fill the output with basis functions which may challenge the interpretation capability of the analyst, but it may do so without regard to non-fit standards of statistical congruency. What is gained in fit, may be lost in validity. Let us see whether this pattern is maintained with the male respondents.

9.1.2 Male Positive Symptom models

To find out what happens with the male respondents, we first examine the graphs of the male positive symptom scale score against cumulative dose over the three time periods. We turn now to the model for the men in the study. But before we perform the statistical analysis, we first graph the measure of mental health dysfunctionality, the Brief Symptom inventory positive symptom subscale score of for the men over our three waves of time.

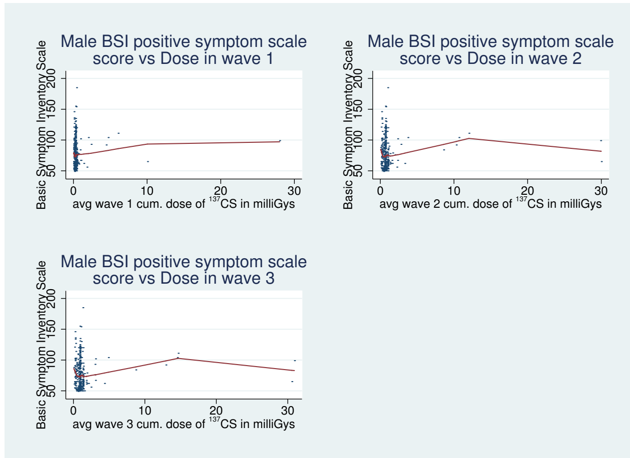

Figure 3: **male BSI positive symptom subscale scores by cumulative ^{137} CS dose over three waves**

We find again that these basic relationships exhibits nonlinearity as well. We might use polynomial or fractional power functions if these turns appeared to be gradual. But the turning points in these graphs are sharp rather than gradual and continuous. Therefore, we look for a method of representing this and find that regression splines, perhaps automatically generated for us by MARS may provide just the right transformations to represent these relationships that we would like to test. So again we turn to MARS to see what it can do to help us explore this aspect of reality.

Before loading basis functions, we obtain a baseline model for male respondents concerning dose and the BSI positive symptom scale. The baseline model contains no basis functions. We observe that only in wave one does there appear to be a dose-positive symptom scale relationship that is statistically significant. In the other two wave, no statistical significance is apparent. What may be just as interesting is the other covariates that are found to be statistically significantly associated with general mental health dysfunction as measured by the BSI positive symptom subscale.

Several aspects of socio-economic status appears to be related to the general mental dysfunctionality positive symptom subscale score according to the results in Table 4. Educational attainment of a bachelor's degree (educ4) or educ7 (a Ph.D.) is positively linked to higher scores on the BSI positive symptom scale for men. Linked to less dysfunction are the martial statuses of cohabiting in wave one (marrw12), being single in wave two (marrw21), being divorced in wave two (marrw24), being married in wave three (marrw33). Also inversely related to such dysfunctionality is being retired in wave two (emplw25). Being a homemaker or caregiver seems positively associated whereas working outdoors (famers, lumbermen, trappers) seems inversely related to such dysfunctionality.

Income sufficiency does not seem to be related for men.

Particular problems plague these men during wave two with significant effects. They include air and water pollution in both waves one and two (airw1 and airw2), and self-reported wave two depression and Chornobyl related health threat to oneself (radhlw2). However, the only dose-positive symptom impact is evident at wave one. The model as measured by adjusted R^2=0.458 is a respectable. But even more important is that only one of the model assumptions is in violation.

Table 4: EQ(13) Modelling BSIposymp by OLS-CS
The dataset is: guys.dta
The estimation sample is: 1 - 340

	Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
Constant	76.0152	4.446	4.030	18.9	0.0000	0.5328
educ4	10.5398	4.830	5.188	2.03	0.0431	0.0131
educ7	-13.1150	9.002	4.358	-3.01	0.0028	0.0282
marrw12	-15.9041	7.535	3.753	-4.24	0.0000	0.0544
marrw21	-12.1409	2.996	3.263	-3.72	0.0002	0.0425
marrw24	-19.2302	10.39	4.196	-4.58	0.0000	0.0631
marrw33	-6.72192	2.293	2.648	-2.54	0.0116	0.0202
childw2	-3.42953	1.581	1.863	-1.84	0.0666	0.0107
emplw25	-14.6481	4.954	4.564	-3.21	0.0015	0.0320
occ6w1	-14.7849	8.032	5.540	-2.67	0.0080	0.0223
occ8w1	-3.04011	2.796	3.050	-0.997	0.3196	0.0032
occ7w3	9.52459	2.796	3.381	2.82	0.0052	0.0248
inc1w1	4.51683	3.031	2.836	1.59	0.1122	0.0081
inc3w2	-2.83038	2.105	2.050	-1.38	0.1684	0.0061
inc4w2	-10.3680	6.052	5.953	-1.74	0.0826	0.0096
inc1w3	-1.23529	3.226	3.836	-0.322	0.7476	0.0003
inc4w3	11.6291	5.642	4.657	2.50	0.0130	0.0196
airw1	-0.0538877	0.03236	0.03894	-1.38	0.1674	0.0061
airw2	-0.108320	0.04605	0.04958	-2.18	0.0296	0.0151
airw3	0.0562605	0.04006	0.04158	1.35	0.1770	0.0058
radchw3	-0.0375368	0.03117	0.02909	-1.29	0.1979	0.0053
radhlw2	0.224384	0.03387	0.04215	5.32	0.0000	0.0833
illw3	6.08420	1.103	1.337	4.55	0.0000	0.0623
depagw1	0.0908117	0.04081	0.06095	1.49	0.1372	0.0071
depagw2	0.269824	0.07069	0.1049	2.57	0.0106	0.0208
avgcumdosew1 U	1.18106	1.284	0.5961	1.98	0.0484	0.0124
avgcumdosew2 U	-1.43189	4.240	2.289	-0.626	0.5320	0.0013
avgcumdosew3 U	0.560894	3.831	2.229	0.252	0.8015	0.0002

sigma	17.0257	RSS	90441.298
R^2	0.501136	F(27,312) =	11.61 [0.000]**
Adj.R^2	0.457965	log-likelihood	-1431.64
no. of observations	340	no. of parameters	28
mean(BSIposymp)	74.9618	se(BSIposymp)	23.1256

When the log-likelihood constant is NOT included:

AIC	5.74822	SC	6.06354
HQ	5.87386	FPE	313.748

When the log-likelihood constant is included:

AIC	8.58609	SC	8.90142
HQ	8.71174	FPE	5358.65

Normality test:	Chi^2(2) =	35.773 [0.0000]**
Hetero test:	F(39,300) =	1.3885 [0.0694]
RESET23 test:	F(2,310) =	0.55927 [0.5722]

```
Table 5 Modelling BSIposymp by OLS-CS
       The dataset is guys.in7
       The estimation sample is: 1 - 340

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
depagw1             0.0422038    0.01124    0.01496     2.82  0.0051   0.0245
BFps1f                1.01014     0.3436     0.5369     1.88  0.0608   0.0110
BFps2f                3.77415     0.4887      1.001     3.77  0.0002   0.0429
BFps4                0.800758    0.09437     0.1582     5.06  0.0000   0.0748
BFps14b               3.54876     0.5376      1.033     3.44  0.0007   0.0359
BFbsidep11         -0.0370855    0.01675    0.01997    -1.86  0.0643   0.0108
BFbsidep12            1.66140     0.1198     0.1356     12.3  0.0000   0.3214
BFbsidep13            2.09106     0.1552     0.2106     9.93  0.0000   0.2373
BFbsidep14            2.30043     0.1575     0.1948     11.8  0.0000   0.3055
BFptsd2a            0.0397467    0.01259    0.01901     2.09  0.0373   0.0136
BF5sociso3           -2.24763     0.3732     0.5600    -4.01  0.0001   0.0484
BFdepx1              0.776016    0.08013     0.1486     5.22  0.0000   0.0792
emplw11               22.1433      4.671      10.71     2.07  0.0395   0.0133
emplw12               16.3055      3.151      8.316     1.96  0.0508   0.0120
emplw13               16.7090      3.211      8.284     2.02  0.0445   0.0127
emplw16               16.9370      3.194      8.240     2.06  0.0407   0.0132
emplw22               1.71709     0.6972     0.6371     2.70  0.0074   0.0224
occ5w2                2.15340      1.128      1.186     1.82  0.0704   0.0103
occ4w3                1.41793     0.8934     0.6351     2.23  0.0263   0.0155
I:180                -35.9714      5.501      3.896    -9.23  0.0000   0.2120
avgcumdosew1  U     -0.678928     0.3604     0.3830    -1.77  0.0772   0.0098
avgcumdosew2  U      0.552981      1.172      1.380    0.401  0.6889   0.0005
avgcumdosew3  U    -0.0585932      1.055      1.196  -0.0490  0.9609   0.0000

sigma                 4.85845  RSS                 7482.62731
log-likelihood       -1007.98
no. of observations       340  no. of parameters           23
mean(BSIposymp)       74.9618  se(BSIposymp)          23.1256
When the log-likelihood constant is NOT included:
AIC                   3.22669  SC                     3.48570
HQ                    3.32989  FPE                    25.2013
When the log-likelihood constant is included:
AIC                   6.06456  SC                     6.32358
HQ                    6.16777  FPE                    430.424


//---------------------------------------------------------------------------
// Basis function legend for positive symptom analysis

//1  BFps1f = max(0, bf4m - 1.19546e-007);  bf4m = max(0, 32 - BSIsoma)
//2  BFps2f = max(0, phobanx - 2.03628e-008);
//3  BFps4 = max(0, 33.7 - WHPer);
//4  BFbsidep11 = max(0, 65.06 - WHPsleep);
//5  BFbsidep12 = max(0, BSIoc - 5);
//6  BFbsidep13 = max(0, BSIanx - 5);
//7  BFbsidep14 = max(0, BSIips - 4);
//8  BFps14b = max(0, 11-BSIphanx);
//10 BFptsd2a = max(0, fdferw2 - 7.17707e-007);
//11 BF5sociso3 = max(0, 25-BSIsoma);
//12 BFdepx1 = max(0, WHPer + 3.14933e-007);

Normality test:   Chi^2(2)  =   18.319 [0.0001]**
Hetero test:      F(37,301) =   6.5782 [0.0000]**
RESET23 test:     F(2,315)  =   20.030 [0.0000]**
```

When we add basis functions to the model, we observe the results in Table 5.

We find no evidence to support a dose-mental health relationship. We observe a tendency of the radial basis functions to dominate the output, with 47.8% of the variables selected are now basis functions. Because we now need variable labels to be able to facilitate an interpretation of the output, we provide a basis function index at the base of the model output.

The assumption violation rate increases again from 33.3% to 100%.

Many other factors appear to be related to general mental health on the part of the males, including depression in 1986 (depagw1 and BF5sociso3), somaticism (BFps1f), lack of sleep (BFbsidep11), anxiety (BFbsidep13 and BFbsi14b), interpersonal sensitivity (BFbsidep14), emotional reaction (BFps4 and BFdepx1), with some obsessive-compulsiveness (BSIdep12) included.

Other than this buffet of ailments, we find aspects of economic security still significantly related to the general mental dysfunctionality. Nevertheless, the wave one employment status of the male is important in explaining the general mental health. Nonresponse is significant as indicated by (emplw11). Full employment is of borderline significance (emplw12, b=16.31, p = 0.05). Part time status is also significant (emplw13, b=16.71, p=.0445), as is being unemployed (emplw16, b=16.94, p=0.041). Even more important is being full employed during 1987-1996, when the economic troubles were taking place (emplw22, b = 1.72, p=0.0074).

Notwithstanding all that, there appears to be no clear evidence of a dose general mental dysfunctionality relationship among the males. The positive symptom subscale of the brief symptom inventory does not necessarily deal with an aspect of mental health that can be very substantial and extremely serious. Let us switch domains to a very substantial and serious form of mental dysfunctionality and see whether the same thing happens in these models as did in the previous ones.

9.2 PTSD models

To test the hypothesis that cumulative dose predicts PTSD among men and women, we examine the addition of truncated regression splines does to the model of dose-PTSD relationship.

First we want to graphically examine the relationship in Figure 4. Not only do we see that the relationship changes over time, but that at first it is characterized by an abrupt turn downward in wave one. In later waves, it more or less straightens out but retains a slight upward slope.

First we run our baseline model before adding the truncated spline transformations. Unlike our previous findings, we find that dose effect relationship seem to be associated with PTSD on the part of the male respondents. This association remains through all three waves.

We find comfort in believing that AutoMetrics has kept those covariates which were significantly related to the endogenous variable and which therefore provide us with the good control against specification error, at least insofar as the Ramsay reset test would have us believe. However, two of the regression assumptions are not fulfilled.

9.2.1 Male PTSD models

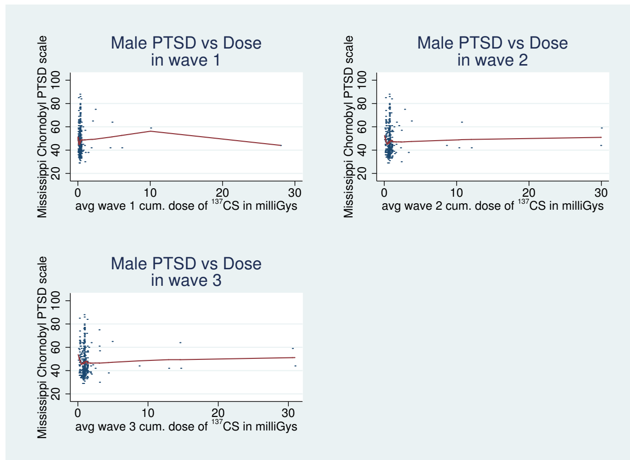

Figure 4: **Male PTSD against Cumulative Effective Dose of ^{137}CS over three waves**

Socioeconomic status appears to play a significant role in PTSD for males. Being employed full-time during wave one (emplw12) is positively associated with PTSD. But part-time employment during wave three (emplw33) is significantly negatively associated with PTSD. For some reason, homemaking and caregiving becomes positively associated with male PTSD in wave three.

Many of these men have experienced some kind of catastrophe in wave three (cataw3) and they report illnesses in waves one and three (illw1 and illw3). There is a significant yet inverse relationship between their belief in the proportion of pollution due to Chornobyl (radchw3) in wave three. They are aware of the hazardous effects of radiation (efradw2) and remain fearful of eating radioactively contaminated food in wave three (fdferw3).

These are men who exhibit significant emotional reactions (WHPer), somaticism (BSIsoma), paranoia (BSIpar), and in wave two they report anxiety (anxagw2). For some reason the direction of significant dose-PTSD relationship switches from inverse to direct and then fades into relative statistical nonsignificance in wave three (p=0.074).

Table 6 EQ(20) Modelling MiPTSD by OLS-CS

The dataset is:/guys.dta

The estimation sample is: 1 - 340

Dropped 1 observation(s) with missing values from the sample

		Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
emplw12		1.74095	0.8400	0.7437	2.34	0.0199	0.0170
emplw25		9.57283	3.406	6.409	1.49	0.1363	0.0070
emplw33		-7.60494	1.677	1.891	-4.02	0.0001	0.0487
occ7w2		-8.96825	3.580	6.720	-1.33	0.1830	0.0056
occ7w3		5.29819	1.689	1.802	2.94	0.0035	0.0266
cataw3		15.0846	3.670	5.033	3.00	0.0029	0.0276
illw1		2.82366	0.9845	1.149	2.46	0.0145	0.0188
illw3		1.56530	0.4444	0.4377	3.58	0.0004	0.0389
shfamw1		-0.00984147	0.009452	0.009251	-1.06	0.2882	0.0036
suchrw3		0.0144091	0.009844	0.009279	1.55	0.1214	0.0076
fdferw3		0.133797	0.01621	0.01669	8.02	0.0000	0.1690
efradw2		0.0607720	0.01242	0.01325	4.59	0.0000	0.0624
radchw1		0.0134653	0.01282	0.01344	1.00	0.3170	0.0032
radchw3		-0.0395825	0.01386	0.01374	-2.88	0.0042	0.0256
WHPer		0.112901	0.03244	0.03768	3.00	0.0029	0.0276
lBSItotal		7.31530	0.4480	0.4154	17.6	0.0000	0.4954
BSIsoma		0.502610	0.09646	0.1127	4.46	0.0000	0.0592
BSIips		-0.337637	0.2135	0.1954	-1.73	0.0850	0.0094
BSIpar		0.393373	0.1629	0.1462	2.69	0.0075	0.0224
anxagw2		0.0638708	0.02325	0.02468	2.59	0.0101	0.0207
avgcumdosew1	U	-1.03625	0.4535	0.3685	-2.81	0.0052	0.0244
avgcumdosew2	U	3.53115	1.577	1.736	2.03	0.0427	0.0129
avgcumdosew3	U	-2.80259	1.423	1.566	-1.79	0.0744	0.0100

sigma	6.1492	RSS	11948.787
log-likelihood	-1084.84		
no. of observations	339	no. of parameters	23
mean(MiPTSD)	47.174	se(MiPTSD)	11.9189
When the log-likelihood constant is NOT included:			
AIC	3.69808	SC	3.95766
HQ	3.80152	FPE	40.3781
When the log-likelihood constant is included:			
AIC	6.53596	SC	6.79554
HQ	6.63940	FPE	689.636

```
Normality test:   Chi^2(2)  =   7.3566 [0.0253]*
Hetero test:      F(40,298) =   1.6234 [0.0133]*
RESET23 test:     F(2,314)  =   1.0049 [0.3673]
```

By adding basis functions, the model becomes considerably less parsimonious. In fact, the number of parameters increases to 65, although there is a huge decline in the residual sums of squares from 11948.787 to 6783.70162. The Schwartz criterion is used as an arbiter, this actually rises from 3.958 to about 4.16 with the addition of the new variables. The only basis function that was added in this case was a linear combination of the dependent variable, which we subsequently deleted from the variable candidate pool.

```
Table 7 EQ(25) Modelling MiPTSD by OLS-CS
       The dataset is: guys.dta
       The estimation sample is: 1 - 340
       Dropped 9 observation(s) with missing values from the sample
```

	Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
emplw12	7.69107	2.819	2.420	3.18	0.0017	0.0366
occ7w2	-5.04297	1.831	1.736	-2.91	0.0040	0.0308
occ7w3	10.3099	2.226	2.254	4.57	0.0000	0.0729
cataw3	8.28971	4.078	2.440	3.40	0.0008	0.0416
illw1	5.17788	0.9376	0.9342	5.54	0.0000	0.1035
fdferw3	0.0302069	0.03236	0.03779	0.799	0.4248	0.0024
efradw2	0.0238300	0.01675	0.01587	1.50	0.1343	0.0084
radchw1	0.0169080	0.01422	0.01504	1.12	0.2619	0.0047
radchw3	-0.0567978	0.01438	0.01427	-3.98	0.0001	0.0562
lBSItotal	4.20572	1.033	0.9615	4.37	0.0000	0.0671
BSIips	-0.911879	0.2381	0.2334	-3.91	0.0001	0.0543
anxagw2	0.0497071	0.02337	0.02327	2.14	0.0336	0.0169
emplw13	5.89476	2.982	2.564	2.30	0.0223	0.0195
emplw16	6.08702	2.940	2.568	2.37	0.0185	0.0207
occ1w1	-2.59177	1.095	0.9997	-2.59	0.0101	0.0246
occ2w2	-3.66632	1.256	1.134	-3.23	0.0014	0.0378
occ3w2	-3.72039	1.623	1.487	-2.50	0.0129	0.0230
occ4w2	-3.96241	1.373	1.072	-3.70	0.0003	0.0489
occ8w2	-2.27052	1.193	1.002	-2.27	0.0243	0.0189
occ1w3	10.7594	2.171	2.255	4.77	0.0000	0.0788
occ2w3	11.5444	2.323	2.244	5.14	0.0000	0.0905
occ3w3	10.5016	2.460	2.383	4.41	0.0000	0.0680
occ4w3	9.37193	2.393	2.131	4.40	0.0000	0.0678
occ5w3	11.9117	2.347	2.450	4.86	0.0000	0.0816
occ6w3	6.08384	3.680	5.175	1.18	0.2408	0.0052
inc2w3	-2.02479	0.9227	0.9335	-2.17	0.0310	0.0174
inc3w3	-2.38019	0.9749	1.008	-2.36	0.0189	0.0205
cataw1	-1.43900	0.9247	0.8904	-1.62	0.1072	0.0097
cataw2	7.34793	3.360	2.425	3.03	0.0027	0.0334
dvcew3	-2.54128	1.302	1.335	-1.90	0.0581	0.0134
illw2	1.16389	0.5908	0.5776	2.02	0.0449	0.0150
movew2	4.36285	0.8182	0.6689	6.52	0.0000	0.1379
shjobw1	0.0436225	0.01294	0.01375	3.17	0.0017	0.0365
shjobw2	-0.0396988	0.01321	0.01286	-3.09	0.0022	0.0346

Table 7 -- continued...

		Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
shhlw2		0.0223050	0.01419	0.01356	1.65	0.1011	0.0101
shfincw2		-0.0219229	0.01411	0.01400	-1.57	0.1187	0.0091
shfincw3		0.0136628	0.01356	0.01175	1.16	0.2459	0.0051
shhousw1		-0.0436495	0.01381	0.01440	-3.03	0.0027	0.0334
shhousw3		0.0403242	0.01213	0.01228	3.28	0.0012	0.0389
shrelaw2		0.0375747	0.01576	0.01483	2.53	0.0119	0.0236
shrelaw3		-0.0429053	0.01358	0.01398	-3.07	0.0024	0.0342
suprtw3		0.00665292	0.008794	0.008390	0.793	0.4285	0.0024
sufamw1		0.0500712	0.01839	0.02032	2.46	0.0144	0.0223
suchrw2		-0.0200943	0.008790	0.009018	-2.23	0.0267	0.0183
fdferw2		0.0793413	0.03196	0.04034	1.97	0.0502	0.0143
kmacc		0.0823621	0.01387	0.02051	4.02	0.0001	0.0572
injothr		1.59261	0.7767	0.8111	1.96	0.0506	0.0143
kmwork		-0.0861868	0.01378	0.02045	-4.21	0.0000	0.0626
polprw3		0.0358676	0.01554	0.01554	2.31	0.0217	0.0196
airw2		-0.0413224	0.01281	0.01355	-3.05	0.0025	0.0338
radw1		0.0322737	0.01101	0.01106	2.92	0.0038	0.0310
radhlw1		-0.0385425	0.01545	0.01560	-2.47	0.0141	0.0224
radhlw3		0.0455350	0.01831	0.01870	2.44	0.0155	0.0218
healthef		0.0176544	0.01307	0.01555	1.14	0.2572	0.0048
icdxcnt		-0.395851	0.2306	0.2331	-1.70	0.0906	0.0107
HP2work		1.58433	0.8974	0.7985	1.98	0.0483	0.0146
HP2hmcare		-2.48808	0.9763	0.8842	-2.81	0.0053	0.0289
HP2pbfhm		1.92806	1.379	1.448	1.33	0.1842	0.0066
BSIposymp		0.382404	0.05583	0.05262	7.27	0.0000	0.1656
BSIdep		-0.617556	0.1875	0.1736	-3.56	0.0004	0.0454
BSIphanx		-1.03931	0.2448	0.2323	-4.47	0.0000	0.0700
BSIhos		-0.425587	0.1974	0.1798	-2.37	0.0186	0.0206
avgcumdosew1	U	0.730692	0.7812	0.5074	1.44	0.1510	0.0077
avgcumdosew2	U	-3.98866	2.462	1.707	-2.34	0.0202	0.0201
avgcumdosew3	U	2.47899	1.851	1.423	1.74	0.0827	0.0113

```
sigma                  5.05001  RSS                 6783.70162
log-likelihood        -969.505
no. of observations        331  no. of parameters           65
mean(MiPTSD)           47.0242  se(MiPTSD)             11.7831
When the log-likelihood constant is NOT included:
AIC                    3.41291  SC                     4.15955
HQ                     3.71070  FPE                    30.5107
When the log-likelihood constant is included:
AIC                    6.25079  SC                     6.99743
HQ                     6.54858  FPE                    521.107

Normality test:   Chi^2(2)  =  0.97273 [0.6149]
Hetero test:      F(104,226)=   1.1353 [0.2170]
RESET23 test:     F(2,264)  =   12.918 [0.0000]**
```

With this model, the hypothesis that dose predicts PTSD is not supported by the data for males at wave one and three The only apparent statistically significant association appears during wave two (avgcumdosew2, b = -3.989, se=2.462,t-prob=0.0202). That wave, covering the years of 1987 through 1996, was one of substantial economic privation and difficulty, during which other stresses and strains may have become more salient in the minds of these men.

What were the significant covariates? One group consisted of socio-demographic characteristics– such as being employed full, part, or unemployed in wave one (emplw12 emplw13 and emplw16, respectively)– were somehow positive associated with Civilian PTSD in wave three.

Some aspects of socio-economic status appear to be related to PTSD in wave three. Having been a professional or administrator in wave one was negatively related to PTSD. In wave two, employment in administrative support or technical sales (occ2w2), the protective services (occ3w2), precision production, mechanical, or crafts fields (occ3w2), or being a student (occ8w2) at the time were negatively associated with PTSD in wave three, as measured by the civilian PTSD scale score. By wave three, such employment – along with employment as a factory laborer (occ5w3) or in agriculture, forestry, trapping, or logging (occ6w3) with the exception of being a student, were positively associated with PTSD. Income sufficiency with resources enough to meet basic necessities plus a little left over (inc3w3) is negatively associated with PTSD. It appears as if socio-economic adequacy may be important.

Some environmental factors may have played a role as well. Males suffering from PTSD were concerned about the distance of their residence and workplace from the scene of the accident (kmacc and kmwork). By wave two, their concerns about air and water pollution (airw2) were inversely associated with PTSD. They were concerned about the Chornobyl related threats to their own health (radhlw3) in wave three, whereas at first any concern they had was inversely associated with PTSD (radhlw1). They were people whose reported illnesses count in waves one (illw1) and two (illw2) were significantly associated with PTSD. Their fear of eating radioactively contaminated food was of borderline statistical significance in wave two (fdferw2 p=0.0502), which became statistically nonsignificant later.

PTSD appears to be positively related to having observed a catastrophic event in wave two or three (cataw2 or cataw3). Their belief in the proportion of radioactively contaminated area is directly related to PTSD. Stresses and hassles from job related matters were in wave one directly associated with PTSD but switched to a significant inverse related relationship in wave two (shjobw1 and shjobw2). Stresses and hassles due to housing matters were inversely related in wave one but directly related in wave three (shhousw1 and shhousw3). Stresses and hassles relating to relationships went from significantly positive to significantly negative in waves two and three (shrelaw2 and shrelaw3).

Forms of support were occasionally related to PTSD in wave three. Family support was significantly only in wave one (sufamw1). Chornobyl survivor support was negatively related to PTSD in wave two (suchrw2).

These were individuals who exhibited general mental health dysfunctionality (BSIposymp) whose health problems impacted their work (HP2work). Bot of these traits were significantly positively related to PTSD in wave three. There was a significant positive association with PTSD between the log of total BSI. There was a borderline significance in the relationship of having injured others and PTSD ($p=0.0506$). Their reported anxiety in wave two was statistically significant with PTSD in wave three (anxagw2,$b = .049$, $p = 0.034$).

They also exhibited a number of significant inverse relationships between psychological symptomatology and PTSD. These included depression (BSIdep), phobic anxiety (BSIphanx), hostility (BSIhos), interpersonal sensitivity (BSI-ips), and the impact of health issues on home care cooking, and repairs (HP2hmcare). It is possible that the economic difficulties exacerbated the PTSD problems in wave two so that there appeared to be a dose-PTSD male relationship at that time.

9.2.2 Female PTSD models

Before turning to the female PTSD models, it behooves us to graph the relationships observed between PTSD and average cumulative dose over the three waves, shown in Figure 5.

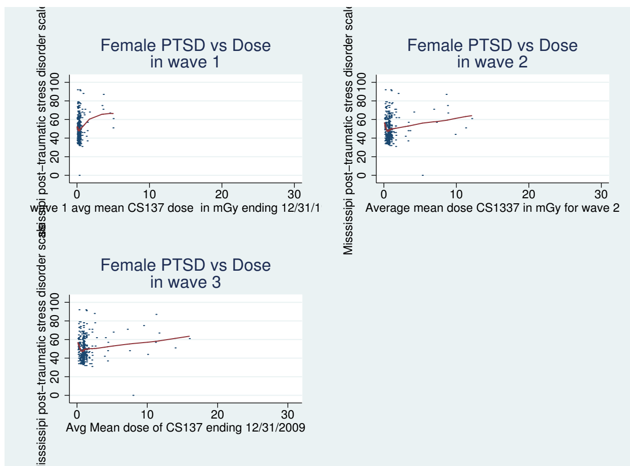

Figure 5: Female PTSD over three waves

Wave one appears to be less linear in functional form than the others, so we may have more need of the basis functions there, but the other two relationships appear to be fairly linear without the need of transformation.

Let's examine the female baseline model explaining PTSD, for our hypothesis test, for stressors, and then for buffers relating to the PTSD.

In the baseline model, we observe no statistically significant relationship between dose as measured by avgcumdose in waves one through three, and PTSD for women as measured by the Civilian PTSD scale score.

For the women, the baseline model is elaborate with 55 parameters. Two-thirds of the first page of output consist in socio-economic attributes. How does socio-economic status relate to PTSD? Some of the largest coefficients indicate salient aspects of socio-economic status related to PTSD. Being single (marrw21)in wave two is significantly directly related to it. Cohabiting (marrw12) in wave one is significantly positively related to it. Income insufficiency (inc1w3) or almost having such insufficiency (inc2w3) in wave three are significantly related to the PTSD. Having a child in wave one is significantly inversely related to it. With respect to occupational status, working outdoors (occ6w1) is significantly related to it in wave two (farming, logging, trapping, etc).

Other stressors are salient. Accidents (accdw1) in wave one are significantly positive related to female PTSD in wave three. Stresses and hassles from relationships (shrelaw1) during wave one are significantly positively related to PTSD. Catastrophes in wave three are positive related to PTSD for women. General mental dysfunctionality as measured by the BSI positive symptom scale is significantly positively related to PTSD. Depression (depagw1 and depagw2) and anxiety (anxagw1 and anxagw2) may be statistically related as well They seem to be significantly related but the signs of their parameter estimate change in opposite directions as we move from wave one to wave two. Health problem interference with interests and hobbies (HP2inthob) is significantly positively associated with PTSD on the part of the female respondents. Consumption of pain pills (pillw2) in wave two seems to be statistically related to PTSD. The geodesic distance of the residence from the accident site (havmil) is also found to be statistically significantly related to PTSD. Also, the stresses and hassles from the job and from relationships appears to be significantly positively related to female PTSD.

Buffers to PTSD are also evident in this model. Having a child in wave one (childw1) for a woman is inversely related to PTSD. Being an MD (occ8w3) is also inversely related to PTSD. Working outdoors in agriculture, logging, forestry, are other jobs inversely related to PTSD (occ6w3). Health issues impacting one's sex life seem to be inversely related to PTSD for women (HP2sxlife). The stresses and hassles from one's health are inversely related to PTSD for women.

Supports also have a role to play. Family support(sufamw2) in wave two is significantly related as is Chornobyl survivor support in wave one (suchrw1). The belief that a large proportion of pollution is due to Chornobyl (radchw3) is significantly positively related to female PTSD.

Table 8 EQ(29) Modelling MiPTSD by OLS-CS
The dataset is: gals.dta
The estimation sample is: 1 - 363
Dropped 7 observation(s) with missing values from the sample

	Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
marrw12	8.24237	4.931	4.806	1.72	0.0873	0.0096
marrw21	12.3299	1.805	1.792	6.88	0.0000	0.1355
marrw22	8.47335	3.703	2.766	3.06	0.0024	0.0301
marrw23	6.23052	1.614	1.725	3.61	0.0004	0.0414
childw1	-1.26565	0.8791	0.7999	-1.58	0.1146	0.0082
childw2	2.55125	0.9794	0.8653	2.95	0.0034	0.0280
emplw13	2.94446	2.047	1.774	1.66	0.0980	0.0090
emplw32	3.52670	1.876	2.169	1.63	0.1050	0.0087
emplw33	4.18612	7.971	1.777	2.36	0.0191	0.0180
occ2w1	2.77946	1.582	1.613	1.72	0.0860	0.0097
occ4w1	-0.606786	2.170	1.844	-0.329	0.7424	0.0004
occ6w1	13.1978	4.550	2.815	4.69	0.0000	0.0678
occ6w2	-9.92894	4.473	2.773	-3.58	0.0004	0.0407
occ8w2	-5.30301	2.045	2.187	-2.42	0.0159	0.0191
occ8w3	-9.21187	8.387	2.808	-3.28	0.0012	0.0344
inc1w3	8.22857	1.680	1.812	4.54	0.0000	0.0639
inc2w3	8.85438	1.391	1.337	6.62	0.0000	0.1267
inc3w3	7.71199	1.413	1.372	5.62	0.0000	0.0947
deaw1	1.16721	0.5685	0.6472	1.80	0.0723	0.0107
deaw2	-0.631489	0.5636	0.5662	-1.12	0.2656	0.0041
dvcew3	-5.08077	1.884	1.790	-2.84	0.0048	0.0260
sepaw2	-5.42709	3.268	2.621	-2.07	0.0392	0.0140
sepaw3	7.34660	2.257	2.257	3.26	0.0013	0.0339
accdw1	8.14050	2.308	1.849	4.40	0.0000	0.0603
accdw3	4.52347	1.349	1.181	3.83	0.0002	0.0463
cataw1	-2.97149	1.501	1.410	-2.11	0.0359	0.0145
cataw3	9.48043	5.937	5.320	1.78	0.0757	0.0104
shjobw1	0.0459037	0.01897	0.02220	2.07	0.0395	0.0140
shfamw2	0.0173869	0.02005	0.02067	0.841	0.4010	0.0023
shhlw1	-0.0632661	0.01947	0.02554	-2.48	0.0138	0.0199
shhlw3	0.0113486	0.01642	0.01671	0.679	0.4976	0.0015
shfincw2	-0.0151884	0.02226	0.02365	-0.642	0.5212	0.0014
shfincw3	-0.0204790	0.01681	0.01948	-1.05	0.2941	0.0036
shrelaw1	0.0579751	0.01556	0.01523	3.81	0.0002	0.0458
sufamw3	0.0354931	0.01329	0.01453	2.44	0.0151	0.0194
suchrw1	0.0885848	0.04288	0.04238	2.09	0.0374	0.0143
pillw2	0.246420	0.1558	0.1249	1.97	0.0493	0.0127
pillw3	-0.132645	0.09234	0.09077	-1.46	0.1450	0.0070
injselfr	1.48063	1.100	1.147	1.29	0.1978	0.0055

Table 8 - continued...

explanatory var		Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
radchw1		-0.00608758	0.01568	0.01719	-0.354	0.7234	0.0004
radchw3		0.0455101	0.01787	0.01961	2.32	0.0210	0.0175
WHPer		0.0124274	0.03620	0.04239	0.293	0.7696	0.0003
HP2pbfhm		-2.00175	1.695	1.999	-1.00	0.3176	0.0033
HP2sxlife		-5.74679	1.371	1.523	-3.77	0.0002	0.0450
HP2inthob		7.84715	1.583	2.314	3.39	0.0008	0.0367
BSIposymp		0.292820	0.02081	0.02386	12.3	0.0000	0.3328
havmil		0.00610682	0.001950	0.002717	2.25	0.0253	0.0165
depagw1		-0.0666916	0.02328	0.02283	-2.92	0.0037	0.0275
depagw2		0.109470	0.03546	0.03460	3.16	0.0017	0.0321
anxagw1		0.0455276	0.01835	0.01819	2.50	0.0128	0.0203
anxagw2		-0.0720609	0.02882	0.03571	-2.02	0.0445	0.0133
avgcumdosew1	U	3.03671	1.669	1.928	1.57	0.1164	0.0081
avgcumdosew2	U	2.25711	2.073	2.156	1.05	0.2960	0.0036
avgcumdosew3	U	-2.93719	1.507	1.815	-1.62	0.1067	0.0086

sigma	7.70878	RSS	17946.4376
log-likelihood	-1202.94		
no. of observations	356	no. of parameters	54
mean(MiPTSD)	49.6208	se(MiPTSD)	12.0886

When the log-likelihood constant is NOT included:

AIC	4.22359	SC	4.81136
HQ	4.45739	FPE	68.4392

When the log-likelihood constant is included:

AIC	7.06146	SC	7.64923
HQ	7.29527	FPE	1168.91

```
Normality test:   Chi^2(2)  =   4.9117 [0.0858]
Hetero test:      F(81,272) =   1.1388 [0.2219]
RESET23 test:     F(2,300)  =   37.383 [0.0000]**
```

When we mix AutoMetrics with MARS for the PTSD hypothesis test for females, we obtain a rather elaborate and no very parsimonious model. We note that the hypothesis that dose is directly associated with PTSD measured by the Civilian Mississippi scale is consistent with parameter estimates for cumulative dose of ^{137} CS in mGys (avgcumdosew1 and avgcumdosew3, both of which are statistically significant at the 0.05 level).

```
Table 9 EQ(32) Modelling MiPTSD by OLS-CS
       The dataset is:gals.dta
       The estimation sample is: 1 - 363
       Dropped 5 observation(s) with missing values from the sample
```

	Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
marrw10	2.40743	3.127	2.103	1.14	0.2533	0.0044
marrw12	8.70104	3.872	4.456	1.95	0.0518	0.0126
marrw13	3.79369	1.166	1.149	3.30	0.0011	0.0351
marrw21	3.82439	1.410	1.323	2.89	0.0041	0.0272
marrw25	7.03501	3.217	2.954	2.38	0.0179	0.0186
marrw32	-4.37927	2.753	1.800	-2.43	0.0155	0.0194
marrw35	-5.37582	1.928	2.308	-2.33	0.0205	0.0178
childw1	-0.595462	0.5982	0.7546	-0.789	0.4307	0.0021
emplw13	3.04047	1.861	1.736	1.75	0.0810	0.0102
emplw15	5.87467	3.790	2.599	2.26	0.0245	0.0168
emplw22	2.45999	1.227	1.047	2.35	0.0194	0.0181
emplw25	-3.04349	2.065	2.118	-1.44	0.1518	0.0069
emplw33	8.96577	7.031	2.166	4.14	0.0000	0.0542
occ3w1	-5.70773	1.423	1.598	-3.57	0.0004	0.0409
occ6w1	5.11728	2.547	2.332	2.19	0.0290	0.0159
occ2w2	2.73149	1.220	1.465	1.86	0.0632	0.0115
occ7w2	5.13912	1.805	1.523	3.38	0.0008	0.0367
occ8w2	-3.99304	1.859	1.748	-2.28	0.0231	0.0172
occ8w3	-7.08976	6.967	1.908	-3.72	0.0002	0.0442
inc1w3	2.59772	1.277	1.311	1.98	0.0485	0.0130
inc2w3	2.52167	0.9265	0.9327	2.70	0.0073	0.0239
deaw2	-0.776765	0.5023	0.5270	-1.47	0.1416	0.0072
dvcew1	3.21334	5.055	2.772	1.16	0.2473	0.0045
dvcew2	-6.65500	2.146	1.942	-3.43	0.0007	0.0378
sepaw1	-11.6999	5.853	5.004	-2.34	0.0200	0.0180
sepaw3	5.04579	1.756	1.970	2.56	0.0109	0.0215
accdw1	8.29547	1.976	2.055	4.04	0.0001	0.0517
accdw3	4.28951	1.165	1.373	3.12	0.0020	0.0316
cataw3	12.6758	5.373	5.723	2.21	0.0275	0.0161
illw3	1.44130	0.4337	0.4956	2.91	0.0039	0.0275
movew3	1.88537	2.146	1.747	1.08	0.2813	0.0039

Continued on the next page...

Table 9 continued from previous page ...

		Coefficient	Std.Error	HACSE	t-HACSE	t-prob	Part.R^2
shjobw1		0.0507772	0.01648	0.01829	2.78	0.0058	0.0251
shjobw3		0.00812849	0.01277	0.01383	0.588	0.5572	0.0012
shhlw1		-0.0444529	0.01734	0.02059	-2.16	0.0317	0.0153
shfincw1		0.0448605	0.01388	0.01257	3.57	0.0004	0.0408
shfincw3		-0.0395446	0.01394	0.01599	-2.47	0.0139	0.0201
suprtw2		-0.0222859	0.009940	0.009618	-2.32	0.0212	0.0176
sufamw3		0.00922673	0.01160	0.009733	0.948	0.3439	0.0030
pillw3		-0.114727	0.06201	0.04760	-2.41	0.0165	0.0191
airw1		0.0250637	0.01327	0.01270	1.97	0.0494	0.0129
radchw1		-0.0600910	0.01499	0.01546	-3.89	0.0001	0.0481
radchw3		0.0758247	0.01561	0.01648	4.60	0.0000	0.0661
WHPsleep		0.0585702	0.01677	0.01846	3.17	0.0017	0.0326
WHPsociso		-0.0184077	0.02557	0.02705	-0.680	0.4967	0.0015
HP2sxlife		-4.72120	1.209	1.364	-3.46	0.0006	0.0385
HP2vacatn		5.48797	1.353	1.482	3.70	0.0003	0.0439
BSIposymp		0.208521	0.01950	0.02045	10.2	0.0000	0.2579
depagw1		-0.0678127	0.02029	0.02263	-3.00	0.0030	0.0292
depagw2		0.100628	0.03216	0.03028	3.32	0.0010	0.0356
anxagw1		0.0612168	0.01615	0.01665	3.68	0.0003	0.0432
anxagw2		-0.157812	0.03253	0.03638	-4.34	0.0000	0.0592
BFptsd5		0.266666	0.04240	0.03959	6.74	0.0000	0.1318
BFptsd2a		0.277405	0.03833	0.03685	7.53	0.0000	0.1593
BFptsd4a		0.0842508	0.04848	0.04852	1.74	0.0835	0.0100
BFptsd5a		-0.0270958	0.01449	0.01617	-1.68	0.0949	0.0093
BFptsdw33		0.0974791	0.03504	0.03758	2.59	0.0100	0.0220
avgcumdosew1	U	4.28430	1.459	1.855	2.31	0.0216	0.0175
avgcumdosew2	U	2.65230	1.847	1.800	1.47	0.1417	0.0072
avgcumdosew3	U	-3.54964	1.341	1.492	-2.38	0.0180	0.0186

```
sigma                  6.68318  RSS                 13354.8046
log-likelihood         -1155.8
no. of observations        358  no. of parameters           59
mean(MiPTSD)           49.6117  se(MiPTSD)             12.0553
When the log-likelihood constant is NOT included:
AIC                    3.94871  SC                     4.58824
HQ                     4.20305  FPE                    52.0259
When the log-likelihood constant is included:
AIC                    6.78658  SC                     7.42611
HQ                     7.04093  FPE                    888.574

Normality test:   Chi^2(2)  =   5.0543 [0.0799]
Hetero test:      F(88,267) =   1.4085 [0.0201]*
RESET23 test:     F(2,297)  =   1.4425 [0.2380]

Basis function legend:
BFptsdf =
BFptsd5 = max(0, 70-fdferw2)
BFptsd4a = max(0, 40 - depagw3)
BFptsd5a = max (0, airw2-10)
BFpstdw33 = max(0, anxagw3)
```

To summarize the female analysis, we will note some salient significant stressors and buffers for PTSD among women in several domains–that of socio- economic status (SES), that of major negative life events, that of daily stresses and hassles, environmental factors, and psychological sequelae. Using the partial R^2

as a form of beta weight, we see that within the domain of SES, being married in wave 1 (marrw13), being divorced in wave 2 (marrw25), unemployed in wave 3 (emplw35), and having a Ph.D. in wave 2(occ7w2) are major stressors relating to PTSD. Other SES stressors are income insufficiency for basic needs or borderline income sufficiency for basic needs in wave three (inc1w3 and inc2w3).

Prominent socio-economic status buffers are being retired in waves 2 and 3 (emplw25 and emplw35) and being a medical doctor in waves two and three (occ8w2 and occ8w3).

Among the major negative life events, several salient stressors appear. Some of the worst are getting separated in wave one (sepaw1) and getting a divorce in wave two, that time of economic tribulation (dvcew2). However, accidents in wave one (accdw1) and three (accdw3) also emerge as substantial stressors.

Within the domain of daily stresses and hassles, financial ones in wave 1 are significantly positively related to PTSD. The reception of Chornobyl support in wave two and the consumption of pain pills in wave three (pillw3) not surprisingly appear to work as buffers.

As for environmental or contextual effects, in wave one the percent belief air and water pollution (airw1) is dangerous is related to PTSD, as is the proportion of pollution due to Chornobyl is high in wave 3 (radchw3) appears to be significantly negatively related to PTSD, although there was a belief that the air and water pollution was dangerous in wave one (airw1) and wave 2 (BFptsd5a), whereas by wave three the direction of this relationship reversed itself, so that it became a significantly positive in wave 3.

Fears of eating contaminated food appear to be significantly positively related to PTSD in wave 2 (BFptsd5).

Psychological symptoms appeared in depression and anxiety in waves one and two (depagw1 and depage2), where they went from inverse to direct over those two waves. However, anxiety went from positive to negative as people became used to the situation from wave one to wave two (anxagw1 and anxagw2). The basis functions reveal that depression and anxiety in wave three were related to PTSD as well.

These effects impacted the sleep, sex life, and vacation plans of the female respondents such that even general mental dysfunction became significantly positively related to PTSD. When the nature of the situation is considered, these women may not seem so unreasonable, after all.

10 Discussion

We will discuss our findings regarding our hypothesis tests. Then we will discuss their reliability, depending upon whether we used the GETS procedure or the mixed MARS and AutoMetrics procedure.

Table 2: **Model Comparisons**

l **Male models**	**Female Models**
Brief symptom inventory positive symptom subscale	
RSS1= 90441.298 NP1 = 28 SC1 = 8.9014 PctViols1=33.3%	RSS1 = 180526.366 NP1 = 21 SC1 = 9.399 PctViols1 = 25%
RSS2 = 7482.627 NP2 = 23 SC2 = 3.486 PctViols2 = 100%	RSS2 = 16814.877 NP2 = 14 SC2 = 4.06295 PctViols2 = 75%
Change :	
ChRSSm = 82,958.671 ChNPm = 5 ChSCm = 5.4154 ChPVm = -67%	ChRSSf = 163711.489 ChNPf = 7 ChSCf = 5.3365 ChPVf = -50%
Civilian PTSD scale score	
RSS1 = 11,948.787 NP1 = 23 SC1 = 3.958 PctViolsm= 66.67%	RSS1 = 14,626.285 NP1 = 55 SC1 = 4.623 PctViolsf = 33.3%
RSS2 = 6,783.702 NP2 = 65 SC2 = 4.160 PctViols2 = 33.33%	RSS2 = 13354.805 NP2 = 59 SC2 = 4.588 PctViols2 = 66.67%
Change :	
ChRSSm =5,165.085 ChNPm = -42 ChSCm = -0.202 ChPctViolsm= 33.33%	ChRSSf = 1271.48 ChNPf = -4 ChSCf = 0.035 ChPctViolsf = -33.33%
legend 1 = baseline model without basis functions (RSS = residual sum of squares for model SC = Schwartz criterion Ch prefix = change score	2= model with basis functions NP = number of parameters PctViols = % of assumptns tested & failed f and m suffix refer to males or females

10.1 Hypothesis tests

To summarize our findings,we divide our hypotheses into two groups– those pertaining to general mental dysfunctionality and those relating to PTSD. We furthermore subdivide them into purely AutoMetrics tests with no basis functions and tests with MARS generated. basis functions and our regular variables with AutoMetrics doing the variable selection. We refer to the later as mixed AutoMetrics and MARS tests.

We have six baseline tests with no basis functions and we have six tests with basis functions. In all but one of our tests, we observe no statistically significant relationship between cumulative dose of ^{137}Cesium on the one hand and general mental dysfunctionality as measured by the Brief symptom inventory positive symptom subscale. The one exception was in a baseline test of wave one.

For both males and females, only one test across three waves exhibited a statistically significant cumulative effective ^{137}CS dose- BSI positive symptom subscale relationship and that was the wave one baseline test with no basis functions for males. In short, more than 91% of the time, we found no significant relationship between dose and BSI positive symptom subscale score.

The results from the battery of tests of the dose - PTSD relationship were not so pure. We ran tests for each of three waves for both men and women in the form of a baseline model with no basis functions and a model containing basis functions. Out of these 12 tests, five tests of them revealed statistically significant relationships between effective cumulative reconstructed dose of ^{137}CS and PTSD as measured by the Civilian Mississippi Chornobyl PTSD test.

Four of the five statistically significant tests were tests on male respondents for both baseline and mixed variables with basis function models in waves one and two. One female mixed basis function test in wave one also found a statistically significant dose-PTSD relationship. Therefore, in 41.67% of these tests, a significant relationship was found. Wave three was the wave in which no statistically significant tests were found, possibly indicating a fading out of the dose-response effect for PTSD in both males and females.

The implication of these finds is important. If we cannot be sure of a dose-effective response relationship when it comes to general mental dysfunctionality, it is possible that most of the relationship between dose and positive symptomatology is psychological rather than physical. It may be that we can expect much more psychological sequelae than we can physical sequelae.

10.2 Model fit and Parsimony

Generally we find that mixing AutoMetrics and MARS leads to a deterioration of parsimony. Our sample of models is clearly too small from which to draw final conclusions regarding improvement or degradation in model fit and parsimony. It provides heuristic evidence of what we might expect in further analysis, although to arrive a definite conclusions further comparisons will be necessary. In Table 2, we have summarized the improvement in residual sums of squares, the number of parameters, the Schwartz criterion and the percentage of misspecification tests offered by AutoMetrics in the short model summary for these tests.

In the models run on the BSI, there generally was an improvement in parsimony, as the Schwartz criterion generally declined as basis functions were used. However, in the models run to test the hypothesis regarding PTSD, we find that the opposite was true. The model parsimony was degraded by the addition of basis functions in both male and female models. The proportion of misspecification went down in the male models but rose in the female models. Although due diligence was given to fitting, overfitting, and trimming in the MARS program, the same cannot be said of respect of regression model assumptions.

10.3 Advantages of MARS

MARS indicates which variables are related to the dependent variable and the optimal transformation by which this relationship is statistically significant. It automates this process so that it is done for the user. MARS now does this with the help of basis functions made up of truncated regression splines. MARS not only determines how many knots are needed for a spline function; it determines where they are placed as well [21, 15]. With AutoMetrics this aspect of variable selection is left up to the user.

MARS identifies interaction terms and the degree of interaction. To some extent AutoMetrics does this when it performs the White specification tests. But it does not go farther than that for testing potentially significant interactions. Moreover, the interactions MARS defines need not conform to conventional interaction definition, so the user must be careful.

MARS systematically develops basis functions that are added to the model to optimize its fit. One advantage of MARS is that sharp turning points can easily be accommodated by regression splines. If the knots in the turning points are not evenly spaced, a polynomial spline would not be able to accommodate such a nonlinear trend. Moreover, a higher order polynomial would of necessity have a lot of multicollinearity within it, and at some point the application of it would become inestimable. However, the basis functions are easily and rapidly computed, according to Lewis and Stevens [17, 865].

MARS will point out areas for further investigation and even variables that the user may have overlooked when he or she formed the candidate regressor pool. Moreover, MARS will endeavor to order the variables in terms of their importance to the model and this is a real advantage for the data miner or anyone exploring the field for the first time.

MARS does offer a select dialog box which allows the analyst to select cases according to their classification on a variable of choice. We can therefore perform male and female analysis separately be selecting according to gender.

10.4 Disadvantages of MARS

Unlike AutoMetrics which uses a multi-path search, MARS models are path dependent. Because it uses a stepwise algorithm, the next basis function selected depends on what has been incorporated before. If the first choice was not optimal, perhaps because of a false positive statistical inference, it is possible that the full model will not be optimal as well.

MARS does not guarantee that the regression assumptions of the model will be met. It merely attempts to optimize the fit, with one of several criteria. It can use MSE or it can use 10-fold cross-validation. Often it constructs basis functions that are combinations of dependent as well as independent variables. The new user must be careful not to have some for of the same variable on both sides of the equation, even when one is a basis function of the other if one is to avoid simultaneity bias.

The common high collinearity of the basis functions and variables tends to slow down processing time considerably, with some computer runs taking hours to complete. Without AutoMetrics, the processing might well abort or cast out highly correlated explanatory variables before completion..

MARS does not guarantee a model with well-behaved residuals. It does not test whether the residuals are normally distributed. It does not mean that there will be homogeneity of residual variance. Nor does it mean that the residuals will not be autocorrelated. It says nothing about ARCH effects or structural breaks or outliers in the data and how to deal with them. In short, although MARS optimizes fit, it does not guarantee statistical congruence. This may pose a serious problem to the validity of a regression model.

Another drawback is that we have to be able to interpret basis functions or these hockey stick transformations of the original variable. In many cases, the variable has been re-centered with a knot placement at an optimal point along its domain to accentuate the part of its slope that is linear and positive. More often than not, the user will have to specify his own legend at the bottom of the regression output where basis functions have been used so he can interpret the regression output if he is mixing AutoMetrics and MARS in this way.

Another problem with MARS is that it will form interactions when only one of the main effects is already in the model. MARS forms its interactions by combining a pair of basis functions with one that is already in the model[21, 34]. This does not lend itself to a proper interpretation of interaction as a joint effect over and above the individual main effects. If one of the main effects is not in the model, then it may not be controlled for, so that the product vector need not represent an effect over and above both of the main effects. Moreover, MARS interactions are not conventional interactions. They are interactions between the positive portions of the component basis functions bounded by knot locations rather than with the complete variable. Therefore, we have to review the model and adjust it to deal with interaction misspecification if we allow MARS interaction generation. We did not do that at this juncture. We will test mediating and moderating effects at the same time very soon.

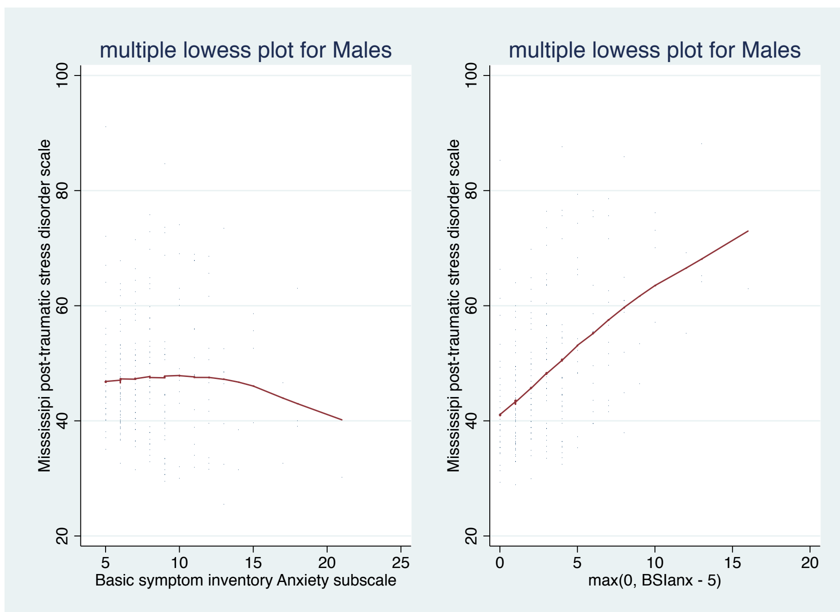

Figure 6: Comparison of PTSD anxiety relationship before and after generation of the basis function

10.5 A warning about using both AutoMetrics and MARS together

Our dataset contains more than 2700 variables and some of the runs require that the computer package be able to handle more variables than observations. AutoMetrics through blocking and chunking of data can perform analysis that involves more variables than observations.

After running MARS on our data, and generating the basis functions that could optimize the fit, we insert those functions into the model selected by AutoMetrics. We ran it through AutoMetrics again and let AutoMetrics decide which of the variables to retain in the model, in accordance with its system of specification searches and regression assumption tests.

We use AutoMetrics to provide the veto control over the misbehavior that can be generated by MARS. If MARS constructs a lot of basis functions that show no respect for fulfillment of the the regression model assumptions, then the proportion of violations of misspecification tests may rise, much to the user's dismay if he is and should be concerned about statistical congruency.

We thought it important to use an exploratory tool that was atheoretical to be sure that we explored all relevant aspects of the subject material, the findings from which may be important to those concerned. We wanted to be fair and honest for all parties concerned as this subject matter might be the basis of policy decision-making in the future.

Although we believe that we have captured the essence of the subject for the variables that we have, we would warn others that combining these two packages may result in longer wait times for the completion of the computer runs as AutoMetrics deals with the collinearity problems created. If there is a means of having your computer beep loudly after the completion of the computer run, this would be the time to make some tea or coffee and do something else while the program takes time to complete.

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