A Review of Salient Ukrainian Psychological Sequelae following Chornobyl

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1 Acknowledgements

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2 Introduction

On April 26, 1986 the Chornobyl nuclear plant in the Ukraine experienced a tragic breakdown that resulted in a meltdown of one of the reactors and the release of a variety of radioactive isotopes into the atmosphere. For a period of four days, the Soviet Union refused to publicly admit what happened. Eventually, it became clear that there had been a meltdown at the Chornobyl plant in Kiev.

3 Objectives

In general our goal is to study the threat of external radiation exposure and the collective psychological response during and after the Chornobyl nuclear incident and to develop a means by which this can be predicted. In a long-term retrospective longitudinal study, we examine the risk of physical exposure to the external radioactivity and perceived risk of exposure separately for males and females.

3.1 Reconstruction of external radiation dose

In general we wish to study the actual external and perceived risk of radiation exposure after the Chornobyl nuclear incident on a population living nearby. More specifically, we would like to examine the nature of the external radiation exposure to the residents of Kiev and Zhytomyr Oblasts. The Chornobyl nuclear plant was located in the north-eastern part of the Kiev Oblast, and the Zhytomyr Oblast is located to the west of Kiev Oblast within the Ukraine. To do so, we need to reconstruct the external radiation dose of ^{137} Ceasium in mGy to which each respondent has been exposed. This isotope of Ceasium is used as a marker indicator because it is easy to distinguish from others, easy to measure and reconstruct, and can be used as basis for the inference of other isotopes if the need arises, as well.

3.2 Perceived risk of exposure

Following the Chornobyl event in April 26, 1986, there was pronounced concern on the part of the residents living nearby as to the damage of the effects to their health, the health of their family, and its effect on the number of cancer cases within the two Oblasts. When the responses to these questions were combined, we had a measure of the perceived health risk from Chornobyl to the self, family, and community. Assessments of the perceived risk were taken in 1986, in the decade that followed, and the time since then. We call these time periods waves 1, 2, and 3, respectively.

3.3 Salient psychological sequelae: Anxiety, Depression, and PTSD

Respondents were asked whether they exhibited symptoms of anxiety, depression, and post-traumatic stress syndrome (PTSD) and when these changed over time. From these recollections, we were able to construct an annual time series of the level of these symptoms from 1980 through the time of the interview conducted in the years 2009 through 2011.

3.4 Models of psychological sequelae based on perceived risk and external dose

Using state space models, we endeavor to develop a method useful in predicting psychological health on the basis of perceived risk, external dose, and other events impacting the measures of psychological sequelae.

3.5 Predictive and diagnostic validation

We hope to assess the predictive validation of these self-reported measures of psychological sequelae and to find their association with well-established valid diagnostic instruments.

4 Analytic approach

In response to the threat from Chornobyl, the respondents reported different the psychological responses over time. In Figure 1, we observe that the male and female responses general differ with respect to these psychological sequelae. All psychological sequelae peak at the instance of the Chornobyl incident. They then abruptly decline and drift from there. None of these sequelae falls back to a pre-Chornobyl level. All symptoms exhibit a level shift upward after 1986, from which point they exhibit a drift. Although PTSD symptoms appear to exhibit a more or less level steady drift after 1986, anxiety and depression appear to drift slightly upward. Although the shifts between 1986 and the decade thereafter are clearly significant, the changes from 1996 to those thereafter do not appear to be so significant, with the exception of some end-effect upward around 2005-2010, which preceded the global Great recession by about 3 years.

We attempt a gender-specific analysis of the self-reported psychological sequelae of Chornobyl– specifically, symptoms of anxiety, depression, and post-traumatic stress syndrome (PTSD)– is conducted. We examine principal driving factors that may be statistically responsible for these sequelae, in an endeavor to explore nature of the psychological response to such a nuclear incident.

To facilitate recollection of phenomena over a long time-span, we divided our study into easily recallable time periods. Our first period was in 1986 after Chornobyl. We refer to this part of year 1986 as wave one of our study. The second wave of the study is the decade that follows 1986– from January 1, 1987 to December 31, 1996. The third wave extends from January 1, 1997 to December 31, 2009. All questions were asked over these three waves of time.

From questions asked about beliefs of respondents during these three waves, we constructed a scale of perceived risk of exposure for male and females from a self-assessment of the extent that the health of the respondent, family, and community were believed to have been affected by Chornobyl. We also asked how specific psychological symptoms–such as anxiety, depression, and PTSD–changed from year to year over the study period from 1980 to 2009 and in some cases extending to 2010, displayed in Figure 1. In order to relate these responses to exposure to radiation, we reconstructed the external exposure to which each person was subjected from 1986 until the end of 2009. The time series plot of the reconstructed external cumulative dose in mGy and the rescaled perceived risk on the part of males and females to radiation exposure is displayed in Figure 2.

4.1 Graphical exploratory data analysis

We begin with a discussion of the phenomena that we study since that event. We examine these anxiety, depression, and PTSD separately for men and women in Figures 3 and 4. Regardless of gender, we find that anxiety and depression appear to follow the same time path, whereas symptoms of PTSD are much less common. However, because our study is a retrospective longitudinal study, our variables are at first recollections of symptoms that the respondents exhibited. We employ path analysis to show that these recollections are related to standard instruments measuring these phenomena today. Then we examine both actual and perceived risk of exposure to radiation stemming from Chornobyl and show how these factors are related to the symptoms the respondents recall. We begin by examining the gender specific graphs displaying these phenomena over time.

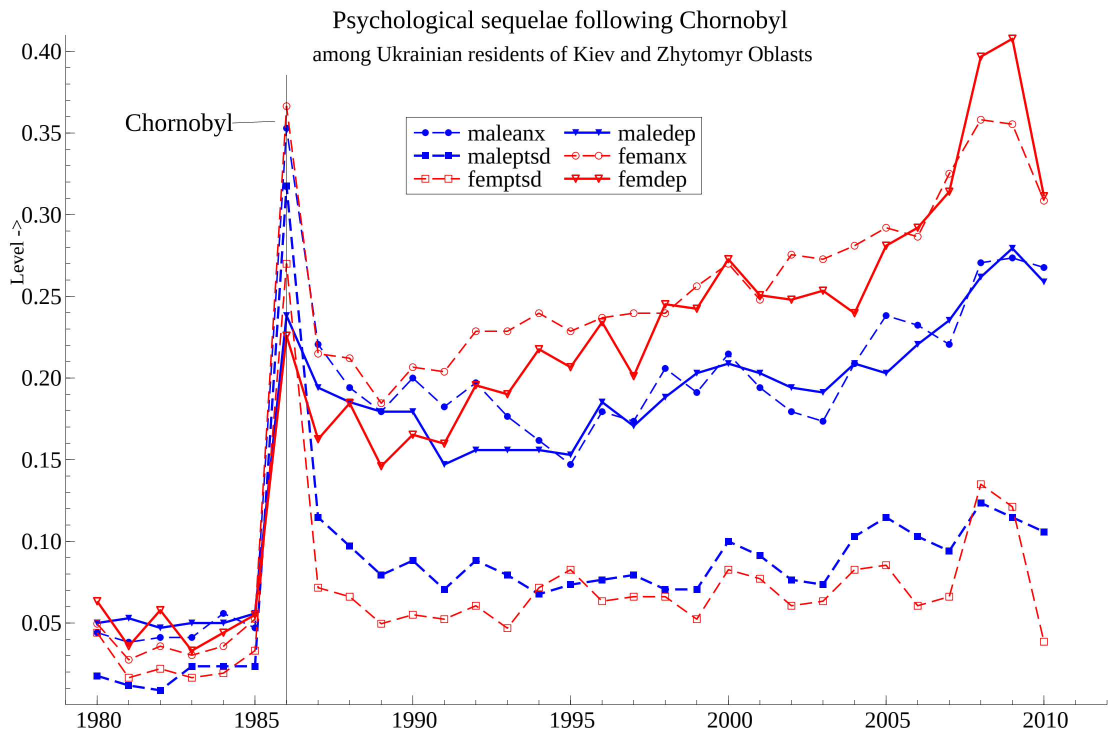

Figure 1: Time series of anxiety, depression, and PTSD among male and female respondents: maleanx = male anxiety; femanx= female anxiety; maledep = male depression; femdep = female depression; maleptsd = male PTSD, and femptsd = female PTSD.

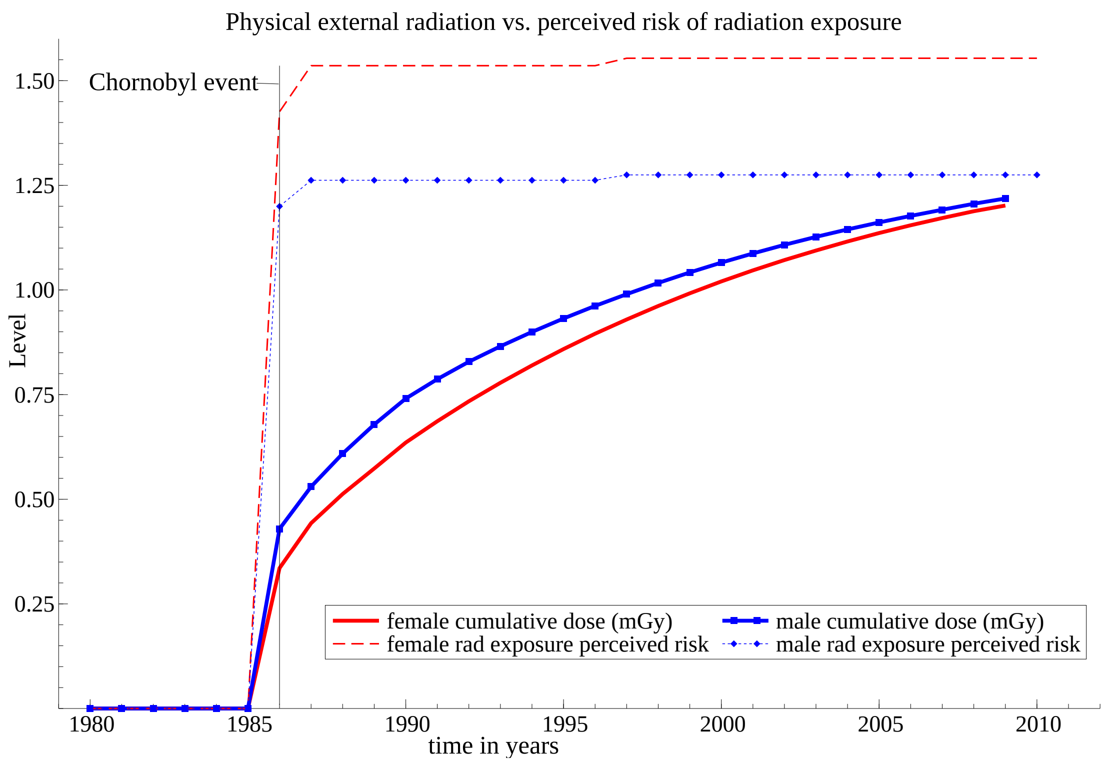

Figure 2: Reconstructed external radiation vs Perceived risk of radiation exposure among Ukrainian residents of Kiev and Zhytomyr Oblasts

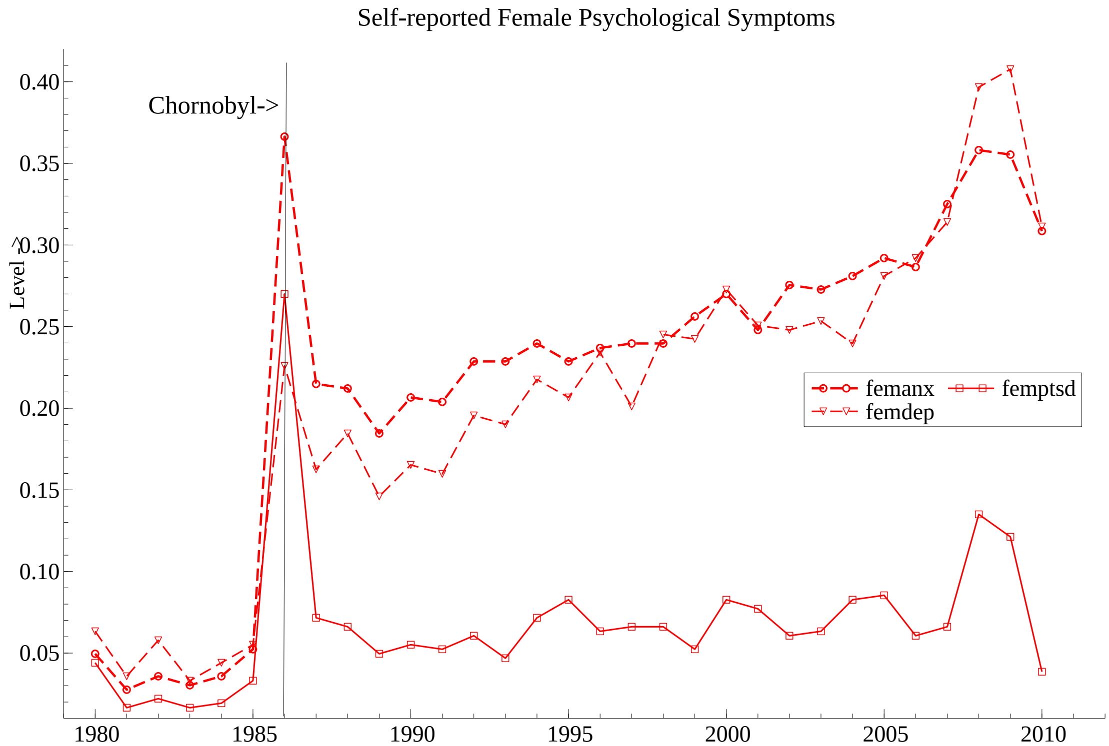

Figure 3: Anxiety, depression, and PTSD among female Ukrainian residents of Kiev and Zhytomyr Oblasts

In Figures 3 and 4, we graphing the anxiety, depression, and PTSD over three periods of time respectively for males and females. We use state space models to analyze the change in self-reported expressions of these symptoms over time since the disaster. The patterns exhibited by these symptoms over time reveal how a representative sample of respondents in the Ukraine psychologically responded to the sudden, surprising, and potentially highly threatening Chornobyl disaster. The exhibited patterns of the magnitude of these effects over time reveal how the public responded to such an event. In so doing, they provide a baseline for evaluation of subsequent events and a sense of how to prepare to manage a similar emergency.

4.2 Assessment of state space model validity

There are three assumptions for state space models. They are in order of their importance independence, homogeneity, and normality.

Independence of the residuals can be tested by tests for autocorrelation–such as the Portmanteau (Box-Ljung Q) tests. Graphically, independence can be visualized by the absence of significant spikes in an autocorrelation function.

$$Q(k) = T(T+2)\sum_{t=1}^{k}\frac{r_t^2}{T-1} \tag{1}$$

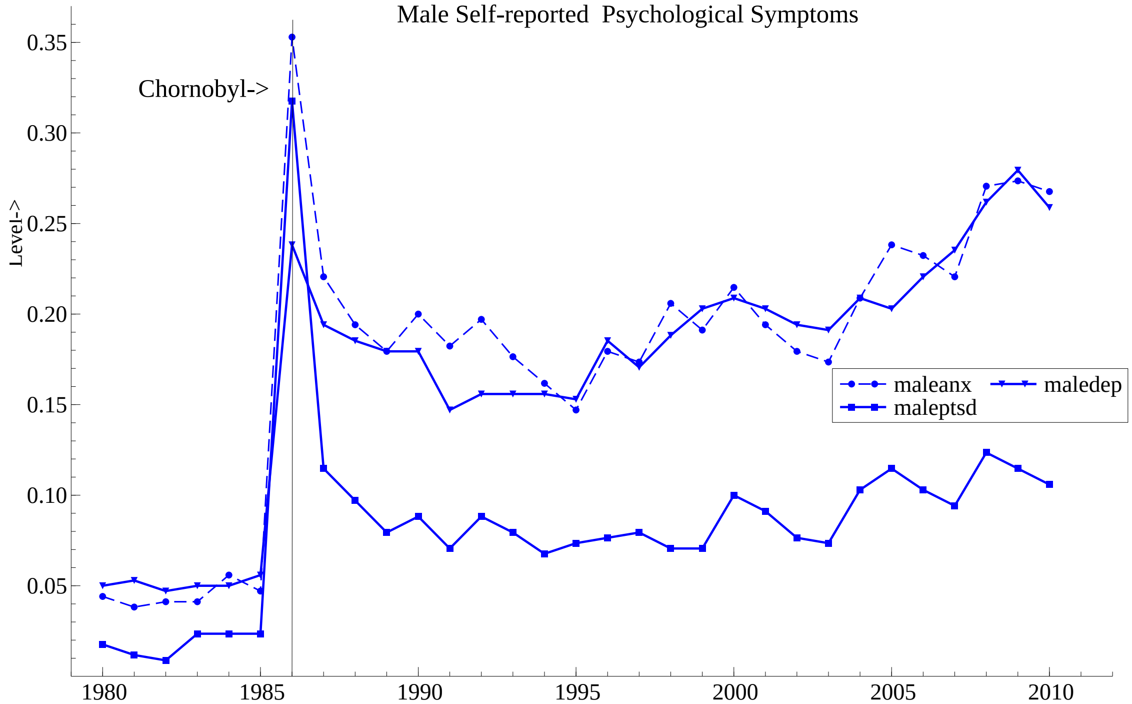

Figure 4: Anxiety, depression, and PTSD among male Ukrainian residents of Kiev and Zhytomyr Oblasts

We can test these assumptions by diagnosing the tests of the residuals. We can use a test for homogeneity by testing the variance of the residuals in the first third of the dataset and comparing it to the variance of the residuals in the third part of the dataset. The ratio of these two variances comprises a F ratio, whose non-significance signifies that the variances are not significantly different from one another and that the series can be considered homogeneous.

The third assumption is that the residuals are normally distributed. A Jarque-Bera test can be used to assess normality of the residuals. This test is a joint test for the normal skewness and normal kurtosis of the residuals. When tested against the theoretical normal, a non-significant result indicates a result that is effectively normal in its distribution.

4.3 Testing for structural breaks

Structural breaks are evidence of phenomena that systematically disrupt the fit of the model. They can be outliers, outlier patches, extended pulses, segmented trends, level shifts, or variance changes that undermine the model stability. If such outliers and level shifts and variance changes are properly modeled, no regime shifts should not undermine the stability of the model. We test for outliers and level shifts with auxiliary residuals, generated by smoothed irregular errors and level errors divided by the square roots of their respective variances [5, 90-96]. We list the results in the Auxiliary residual tables following the residual graphs.

4.4 Predictive validation of the state space model

To assure ourselves of the predictive validity of the model, we evaluate the forecast accuracy. We take the last 8 observations, minus the outliers or level shifts identified, of the model and compare the forecasts with the actual data. This is an in-sample evaluation at first. We can compare accuracy with measures for forecasts of an ex ante forecast. In the latter case, we end our estimation at 2002 and forecast over those next eight observations and then compare the forecasts with the actual data. If there is no statistically significant difference, we infer that the model exhibits predictive validity.

The problem is that there is a global great recession taking place in 2008-2010 and this was the same approximately the time that the Russians were shutting off the gas to the Ukraine. These events may have contributed to increased anxiety and depression, and possibly impacted PTSD as well, but other things might have contributed to this rise in anxiety and depression as well. The investigation of those events might be a subject for future research.

4.5 Diagnostic validation of between self-reports by associations with established diagnostic scales

In this section we use robust path models to identify linkages between self-reports in waves of our study and established diagnostic instruments for identifying the presence of psychological symptomatology. We will also try to test the intraclass correlations as indicators of reliability of these events.

5 Methods

5.1 Research Design

The research design is that of a retrospective panel. Because the respondents were asked to recall phenomena as long as 31 years ago, they were asked to identify the time period in simple segments or waves that were easy to recall and clearly demarcated waves–specifically, the year of Chornobyl, the decade after that disaster, and the time since then. The data we use are self-reported expressions of anxiety, depression, and PTSD. They are particularly important as they may predict these symptoms when measured by diagnostic scales. To demonstrate their importance in the prediction of standardized tests, we perform a robust path analysis across three waves of data and their relationship to standard measures of these symptoms.

5.2 Sampling

We undertook a representative sample of residents in the Kiev and Zhytomyr Oblasts in the Ukraine. To area codes supplied by the Ukrainian telephone company, we attached numbers randomly generated by the computer. Each number that was a phone number was called up to four times in the event of a nonresponse, before moving to the next randomly generated number. Volition of participation was confirmed by an independent group before the data was included in the dataset. Confidentiality of responses was assured by removal of name and address data, before the analysis was conducted. A representative sample of 702 respondents was collected.

5.3 Dose reconstruction

A process was developed to reconstruct the dose from penetrating gamma rays emitted by radioactivity deposited on the ground to each individual in the survey as a function of time. The radiation source term was obtained from the Comprehensive Atlas of Caesium Deposition on Europe after the Chernobyl Accident (1998) [7]. This document includes maps showing ^{137}Cs concentration across Europe, presented in equal-area Lambert oblique azimuthal projections.

The electronic version of this Atlas includes each map plate stored in a vector graphics format with multiple layers of information. One of these layers shows isolines representing intervals of equal ^{137}Cs deposition at the time of the accident; an overlaid layer provides a labeled grid corresponding to intersections of latitude and longitude (this is properly referred to as the conjugate graticule).

Software was developed to recover the contour color that specifies the ^{137}Cs concentration at a specified latitude and longitude. This was accomplished by using the intersections of the conjugate graticule as a guide to define a transformation from the original Lambert projection into an equirectangular projection. This transformation was then applied to the map layer which showed ^{137}Cs concentration, which allowed the ^{137}Cs concentration maps to be loaded into a geostatistical database. Conversion tables between published isoline colors and indicated ^{137}Cs concentration were produced. Latitude and longitude coordinates could then be submitted to the geostatistical database in order to recover the ^{137}Cs concentration at an arbitrary location. Where map plates published in the Atlas overlapped, the ^{137}Cs concentration was taken from the map with the most spatial detail; if a location was submitted to the geostatistical database which had no corresponding map data, the closest available ^{137}Cs concentration was used.

A model was created to determine the dose rate at an arbitrary time t for any individual in the study. This model is based on the following sequence of factors: ^{137}Cs concentration at a location (Lat. Long.) at the time of the accident, $C(t_0)$ [7].^{137}Cs concentration, at time, t, based on decay, soil mixing and weathering, C(t). [22]. Conversion to KERMA rate in air, K(t), from penetrating gamma rays based on C(t). [23]. Conversion from KERMA in air-to-dose in person, as a function of age, at time t [22][23],[25],[15],[16]. Modifying factors for time spent outdoors based on occupation and age. [23]. Shielding factors based on residency indoors and typical construction. [23] The data are integrated and presented as the annual dose rate received by each individual in units of mGy/year.

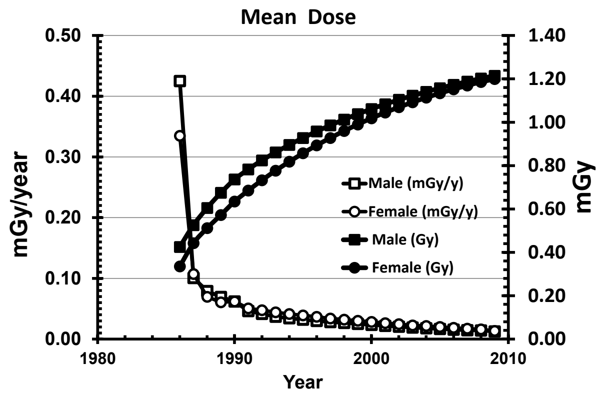

Figure 5: Mean dose

Table 1: Cumulative dose measured in mGy at end of each wave

	12/31/1986	**12/31/1996**	**12/31/2009**
Minimum external dose received	0.0074	0.036	0.047
Maximum external dose received	28.0	30.0	31.0
95th quantile of external dose received	0.037- 1.4	0.14-3.4	0.19-4.4
Mean external dose received	0.38	0.93	1.2
Standard Deviation of External Dose received	1.2	2.0	2.2
Median External Dose received	0.28	0.69	0.91
Mean Natural Background External Dose	0.33	5.3	12.0

Figure 5 shows the results of the dose reconstruction for males and females in terms of annual dose rate (mGy/y) and time integrated cumulative dose (mGy).

The results are summarized in Table 1.

5.4 Measures

5.4.1 Response variables

We used three variables as responses to the disaster. For psychological sequelae variables– specifically, `anxiety`, `depression`, and `PTSD`, we asked respondents about their condition beginning in 1980 to 2009 or the time of the interview. We asked them to advise us of the year of any change in that condition and to what extent the condition changed. Theses estimates are self-reports of the percent of the level of the symptoms experienced. By taking the means of the recalled levels of symptoms, we form a time series of annual means over a 31

Table 2: Alpha reliabilities for perceived risk of exposure by wave

wave	**male**	**female**
1: 1986	0.822	0.761
2: 1987-1996	0.835	0.796
3: 1997-2009	0.841	0.818

year span separately for males and females. We then can analyze the series over time with a view toward identifying temporal patterns as a function of other variables and events over the full span of the study time.

5.4.2 Time-varying regressors

We also constructed variables to be used as stochastic regressors in the models. We developed scales to assess external dose and perceived risk of radiation exposure for males and females. External dose of ^{137} Caesium was reconstructed based on the several factors..

To assess perceived risk of exposure, we form a rescaled model of perceived risk separately for males, designated by `mrpre2` and for females, by `frpre2`. We take the average of three measures of perceived risk for each wave of our study. The three measures include an item reflecting a personal health threat, a family health threat, and a community health threat. More specifically, the first item measures the percent to which one's own health was affected by the Chornobyl incident. The second item measures the percent to which the respondent's family health was affected by Chornobyl. The third item identifies the percent to which cancer cases in the Zhytomyr and Kiev Oblasts were due to Chornobyl. Because these items were averaged, and divided again by 100 to place them on the same scale as the reconstructed external dose, we called them rescaled measures. We assessed the alpha reliability for their scale construction, displayed in Table 2 and graph the scales in Figure 1.

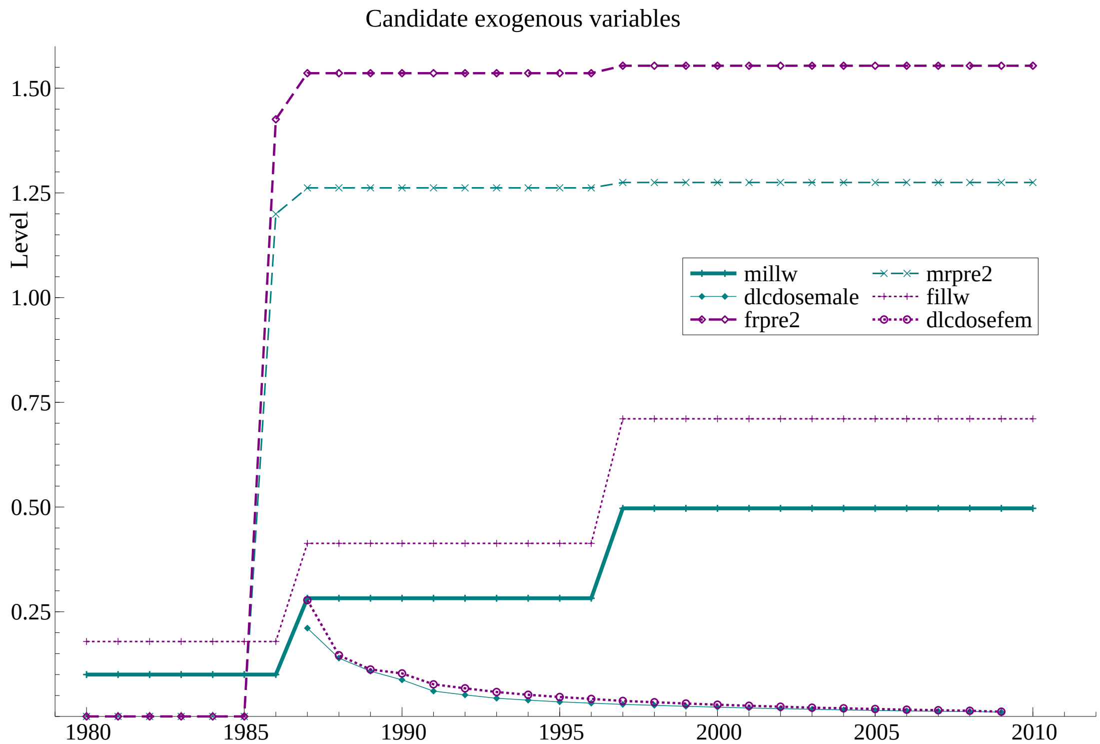

Figure 6: Candidate exogenous variables for male and female respondents

Another measure that we constructed was the gender specific count of physical illness on the part of the respondent. This variable was measured separately for the three waves of the study–respectively, the 1986 period after Chornobyl, for the decade after, and for the time since then to 2009. This was an illness count for males and females asked for each wave of the study. From these variations, average self-reported illness counts for males (`millw`) and females (`fillw`) were also constructed.

5.4.3 Model trimming

Although we endeavored to use all three explanatory variables in our models for psychological sequelae, some of them had to be dropped from the analysis. If the model could not obtain proper starting values for these explanatory variables or if they were not statistically significantly related to the dependent variable being modeled, the problematic explanatory variables had to be dropped from the models being estimated.

Initial models included measures of such explanatory variables reconstructed external dose, the self-report for the frequency of illness on the part of the gender being analyzed, as well as the perceived risk by the gender being analyzed. Attempts to render the reconstructed external dose more stationary natural logged and then first differenced the external cumulative dose. The perceived risk variable was rescaled to place it on more less the same aspect ratio scale as the others for the purpose of graphical display. After the average of the three variables comprising the perceived risk was computed, the rescaling was done by dividing the variable by 100. The rescaling effects allowed the perceived rescaled risk of exposure variable to be depicted in Figure 6.

The net effect of the model trimming was to leave the models oftentimes with some intervention variables, a local level, and one or two stochastic regressors–such as a gender-specific perceived rescaled risk of exposure, and/or occasionally a gender specific self-reported assessment of illness frequency as the driving explanatory variables in the model.

5.4.4 State space models and Mixed frequency analysis

State space models have been used with variables measured a different sampling frequencies and this subject has been discussed in a variety of papers pertaining to mixed frequency model forecasting [1, 2] and [2, 1-3]. Although Bai, Ghysels, and Wright(2010) prefer mixed data sampling (MiDAS) regressors to the Kalman filter, the latter has been used successfully for panel data analysis and may be applied to analysis with mixed frequency data [19] with multiple indicators and multivariate models, where lower frequency sampled data can be treated as missing data to be estimated with the Kalman filter. Although multivariate state space models should be able to handle these problems, in the univariate models that follow we attempt to use state space models to model high frequency data by using lower frequency explanatory variables. They do appear to converge upon sensible solutions, although other configurations may improve upon these results.

5.5 State space models made simple

With these variables, we seek to model and thus explain and possibly predict the psychological sequelae. We use state space models employing an augmented Kalman filter to model an unobserved state vector consisting of local level, irregular, intervention, and stochastic regressors as underlying factors or unobserved components. Mixed frequencies analysis has been used to model lower frequency data [26, 1-3]. We seek to apply the Kalman filter to estimate the unobserved component of a local level model using interventions and time-varying regressors.

State space models are time series models comprising some combination of latent structural components. The components can include time-varying levels, trends, seasonals, or cycles [24, 105]. The models can include fixed event indicators, time-invariant variables and/or stochastic regressors. The basic structural model of a time series consists of a time-varying level, a time-varying slope, and a set of seasonally varying components. The trend component may include a time-varying level and/or slope, whereas seasonal components may be parameterized with seasonal dummy or time-varying trigonometric variables. Depending upon whether these components have measurement error or a random variation, the variables may be fixed or random.

State space system models consist of a process and an observation equation. The process projects the system from one state to the next over time. The observation model defines the factor analysis that connects the observed realization of the data generating process to the latent components comprising it. The components are stacked upon one another in a state vector. That state vector is projected from one state to another by an algorithm tantamount to a one-step-ahead autoregressive forecast of the mean plus a regression on the innovation or error. Inherent in this algorithm is also a mechanism for a Bayesian sequential updating of the variance as well as the mean, usually from a noninformative prior. With a Gaussian assumption for the distribution of residuals, the updated mean and variance are sufficient to reconstruct the realization of the series through a series of recursions designed to minimize the prediction error. This algorithm was developed and published in 1960 by Rudolf Kalman, and by Kalman and William Bucy in 1961.

5.5.1 The Kalman filter

The principal objective of the Kalman filter is to obtain an optimal solution for forecasting or tracking. The model is therefore optimized on the basis of minimizing a prediction error variance rather than an observed error variance. It minimizes the the forecast error and corrects for it in the first pass through the data. After this trajectory has been established, the Kalman smoothing recursion equations uses all of the data for signal extraction and model diagnosis.

The model has two fundamental equations. One is a process equation by which a state vector is moved is from one period to the next. The state vector, α_t, consists of a set of o level, slope, seasonal, cyclical, intervention or event dummies and exogenous variables, entered as components stacked one upon the other within the vector. The process by which this vector goes from one state to the next is an autoregressive process. Koopman, Harvey, Doornik and Shephard [18, 175] explain the process as

$$\alpha_{t+1} = d_t + T_t\alpha_{t-1} + X_t b + H_t\epsilon_t \tag{2}$$

where d_t is an mx1 vector of constants, α_t is an m x 1 state vector, consisting of the structures inherent in the time series, T_t is an mxm transition matrix, H_t is a selection matrix of ones and zeros, and ϵ_t is an $rx1$ vector of forecast errors, and $X_t b =$ where b is a (k + d) x 1 dimensional vector of regression coefficients, with k = the number of stationary stochastic regressors and d = number of nonstationary stochastic regressors) when the state vector is partitioned into stationary and nonstationary elements.

They explain the observation or measurement equation for the state vector for a local level model as

$$y_t = c_t + Z_t\alpha_t + W_t B + G_t\epsilon_t \quad with \quad \epsilon \sim NID(0, \Omega_t) \tag{3}$$

and where

$$\Omega_t = \begin{pmatrix} H_t H_t' & H_t G_t' \\ G_t H_{t'} & G_t G_t' \end{pmatrix} \tag{4}$$

and where B is a $kx1$ vector if all stochastic regressors are stationary, or a $(k+d)x1$ vector if d regressors are nonstationary and the state vector has been partitioned into stationary and nonstationary components.
Forecast errors are computed as [$\nu_t = y_t - E(Z_t\alpha_t - X_t b - \epsilon_t|Y_{t-1})(4) = y_t - Z_t\alpha_t - W_t B$. They show that the variance of $v_t = Var(\alpha|Y_t + Var(\epsilon_t) = P_t + \sigma^2_{\epsilon_t} = F_t$, which can be derived from

$$F_t = Z_t P_{t|t-1} Z_t' + G_t G_t' \tag{5}$$

where y_t = p x 1 observable variable vector, Z_t is a p x m matrix of factor loadings, P_t is an m x m variance-covariance matrix = $Var(\alpha_t|Y_t)$ of the model with starting values

$$\alpha_0 = (a_0, P_0) \tag{6}$$

such that α_0 comprises the prior mean, which equals 0 if this vector is mean centered, and P_0 comprises the prior variance for state vector, which is a very large value if the assumption of a noninformative or diffuse prior is used. These values become the starting values for the filtering process.

5.5.2 Bayesian sequential updating

The filtering process takes place through Bayesian sequential updating. By obtaining expectations from a weighted average of the observation values and the prior values, we obtain the expectations for the mean and variance at the next point in time.

$$\alpha_{t+1} = T_t E(\alpha_t|Y_t), \tag{7}$$

$$and \tag{8}$$

$$P_{t+1} = Var(T_t\alpha_t + H_t\eta_t|Y_t) \tag{9}$$

More specifically, in the case of the local level model, according to Commandeur and Koopman, the Kalman filter recursions update a particular mean, a_1, and variance, P_1, to maximize the likelihood, which can be formulated in as a function of the prediction errors, ν_t and their variances, F_t with a diffuse prior [5, 89]:

$$LL = -\frac{n}{2}log(2\pi) - \frac{1}{2}\sum_{t=d+1}^{n}\left(logF_t + \frac{\nu_t^2}{F_t}\right) \tag{10}$$

so that, according to Durbin and Koopman [12, 28],

$$a_2 = a_1 + \frac{P_1}{P_1 + \sigma_\epsilon^2}(y_1 - a_1) \tag{11}$$

$$P_2 = P_1\Big(1 - \frac{P_1}{P_1 + \sigma_\eta^2}\Big) + \sigma_\eta^2 \tag{12}$$

under the assumption of $\mathrm{P}(\alpha_t|Y_t) \sim N(\alpha_t|P_t)$, with a prior density of $p(\alpha_t|Y_{t-1})$ distributed as $N(\alpha_t, P_t$ and the likelihood is $p(y_t|\alpha_t)$, the posterior density becomes $p(\alpha_t|Y_t)$.

Suppose for a moment that we mean center our variables. We can summarize this process as in a one-step ahead autoregressive forecast with a regression on the innovation where K_t is a regression coefficient, called the Kalman gain:

$$\alpha_{t+1} = T_t\alpha_t + W_t b + K_t\nu_t \tag{13}$$

In other words, K_t is the regression of the state vector upon ν_t, such that

$$K_t = \frac{P_t}{F_t} \tag{14}$$

with the variance updated by a quadratic expression of the variance

$$P_{t+1|t} = T_t P_{t+1|t} T_t' + H_t H_t' - K_t F_t K_t' \tag{15}$$

as Proietti notes [24, 111-114]. The Bayesian sequential updating provides for an incremental adjustment of the accuracy of the filtering process, while maximizing the log-likelihood by minimizing the prediction error decomposition. As this processes iterates to a solution, the Kalman gain K_t approaches a constant called a steady state.

If we assume that we know little or nothing about the prior state, we can commence the updating with a diffuse prior. We obtain starting values for the mean (a_0), which can be the mean of the series or zero if the mean is centered, and the variance (P_0). With a diffuse prior, we would want to use an infinite variance but that could present computational problems. Therefore, a very large number (such as 10^6) is used as a working approximation instead of the ideally infinite variance indicating no certainty about the prior estimate. Eventually, the system will converge to the correct estimate when this is implemented. It merely takes a longer, but with the fast computers we have today, this does not pose an insurmountable problem.

5.5.3 Unobserved components of the structural time series models

In addition to the components of the mean level (μ_t), the slope, (β_t), the seasonality, which can consist of a set of seasonal dummy variables, (γ_t), and/or a set of trigonometric functions (ψ_{it}) to represent long-term cyclical effects, the components of the state vector may include intervention indicators ($\omega_t I_t$) or stochastic regressors, $\lambda_t x_t$.

A fully constituted, α_t the state vector, might consist of:

$$\alpha = \begin{pmatrix} \mu_t \\ \beta_t \\ \gamma_t \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \psi_{1t} \\ \psi_{2t} \\ X_t \\ I_t \end{pmatrix}$$

but it need not. We merely load enough components into the state vector to obtain an accurate representation of the data and thereby preserve parsimonious model formulation.

If we let α_t be a state vector, with c_t and c_t vectors of constants, T_t be a matrix of transition parameter coefficients, R is a selection matrix of ones and zeroes, η_t is a vector of transition errors, and Q_t is an error covariance matrix, we can obtain a transition equation. Furthermore, if we let y_t be a vector of observed variables, and Z_t is a matrix of factor loadings, ϵ_t is a vector of measurement errors, and Q_t is a covariance matrix of measurement errors, then the transition and measurement models may be formulated, respectfully,

$$\alpha_{t+1} = c_t + T_t\alpha_t + W_t b + H_t\epsilon_t \quad y_t \;=\; d_t + Z\alpha_t + X_t b \;+\; G_t\epsilon_t \tag{16}$$

with

$$u_t \sim NID\begin{pmatrix} H_t \\ G_t \end{pmatrix}\epsilon_t \sim NID(0, \Omega_t) \tag{17}$$

so we can stack these matrices prior to processing such that

$$\delta_t = \begin{pmatrix} c_t \\ d_t \end{pmatrix}, \Phi_t = \begin{pmatrix} T_t \\ Z_t \end{pmatrix}, u_t = \begin{pmatrix} H_t \\ G_t \end{pmatrix} \tag{18}$$

resulting in, according to Commandeur and Koopman [5, 136] as

$$\begin{pmatrix} \alpha_{t+1} \\ y_t \end{pmatrix} = \delta_t + \Phi_t\alpha_t + u_t \tag{19}$$

and

$$\Omega_t = \begin{pmatrix} H_t H_t' & H_t G_t' \\ G_t H_t' & H_t H_t' \end{pmatrix} \tag{20}$$

to permit estimation.

5.5.4 The Kalman Smoother

The state vector is estimated via two passes through the data. With a forward pass, using the Kalman filter recursion equations, the state vector finds the optimal starting values from which the state vector can be estimated using past and current values. The predicted or filtered state is thus estimated, iteratively using the data from t=1,..., n.

The output of the forward pass of the filter, subjecting it to a backward pass through all of the data, from t=n,...,1 using state and disturbance smoothers to obtain estimation of the smoothed state and the error variances at a particular time, using all of the data. [5, 84-85]. With all of the data being used, the smoothed estimates are more accurate and smoother than if a mere one-step ahead forecast is being used. The results of these backward recursions are used for signal ($\theta_t = Z_t \alpha_t$) extraction and diagnostic testing with standardized prediction errors (spe):

$$spe = \frac{\nu_t}{\sqrt{F_t}} \tag{21}$$

for such assumptions as independence, homoskedasticity, and normality with autocorrelation, Chow, Jarque-Bera or Bowman-Shenton tests. Disturbance smoothing can be used to generate auxiliary residuals (auxres)

$$auxres = \frac{\hat{\epsilon_t}}{\sqrt{Var(\epsilon_t)}}, \ \frac{\hat{\eta_t}}{\sqrt{(Var(\eta)}} \tag{22}$$

which can be used to identify outliers and structural breaks in the series [5, 93].

5.5.5 Augmentation of the Kalman Filter

To accommodate the nonstationary components, the state vector is partitioned into stationary and nonstationary partitions. Conventional methods are employed for estimation of the stationary partition, whereas the diffuse prior Bayesian sequential updating is employed for estimation of the nonstationary partition.

5.6 Robust path analysis linking our measures to established diagnostic instruments

We endeavor to show that the self-reports exhibit path analytic relations to well-established diagnostic instruments used for identifying presence of psychological symptoms for anxiety, depression, and PTSD. Because the waves embrace long periods of time, natural variation in the level of self-reported symptoms change over time. If we can demonstrate a statistically significant longitudinal path between the self-reports in the third wave and the standard diagnostic measures of the BSI and the MiPTSD, we show that this approach may have current validity.

6 Applications of the Kalman Filter

6.1 Model-building strategy

We analyze anxiety, depression, and PTSD with gender-specific structural time series models. These self-reported psychological symptoms are displayed in Figure 1. The spike in anxiety at the time of Chornobyl is evident for both men and woman in Figures 3 and 4, as it is for depression, and PTSD as well. This shock to the psychological well-being was sudden, potentially- life threatening, and health-threatening is apparent as a graphed outlier for all three responses. Moreover, there was little time to prepare which converted the situation into a frantic to secure oneself, loved ones, and one's property from devastation and degradation.

Model building proceeds from general-to-specific by initial inclusion of all the series that we suspect might be driving or explaining the endogenous psychological sequelae along with any intervention dummy variables that might be necessary to model outliers or level shifts perceived in the introductory time series plots. These series include the differenced natural log of reconstructed external dose, the self-reported illness count, and the perceived risk of exposure to Chornobyl radiation. We also include outliers and level shifts that we observe as important from the graphical exploration of the data–such as, the sudden shock (outlier or blip) or level shift in the series at the onset of Chornobyl incident in 1986. Some indicator of the exponential decline in the magnitude of the series afterward is generally included along with level shifts from year to year as needed. Moreover, also include a measure of level increase after 2008 insofar as it appears in the initial graphs of the sequelae time series.

A review of the auxiliary residuals for the irregular and the level components indicate which significant points need to be modeled with changes in the irregular or level components for ideal model fitting, which may have been ignored up to that point in the modeling process.

To confirm model validation, we diagnosis the model residuals. We examine the correlogram for significant serial correlation, the standardized residuals for evidence of misbehavior, and the cusum-t-tests for variance stability. If the residuals are well-behaved, we have evidence of statistical congruency of model with its assumptions. However, we have to be sure that we have not overfit the data, by increasing the fit to the point that forecasting is impaired. We therefore have to test the model for predictive validity.

To assess predictive validity, we examine the Chow forecast test and the cusum t-test. If these misspecification tests are not statistically significant, we can have some faith in the ex-post forecast validity of the model as well. We conclude by a recapitulation of the salient model characteristics and a comparison of those characteristics among the models.

6.2 Anxiety models

We model the anxiety models for men and women as a function of a local level model with stochastic regressors and interventions. The equations defining the female and male anxiety models are expressed in Equations 24 and 23. They contain anxiety interventions comprising event indicators representing outliers or level shifts in anxiety at the time of the Chornobyl disaster and at time of the great global recession from 2008 to 2009. They also contain the regression effects tested in the final state in 2010. We attempted to include external exposure to radiation formales and females as well as differenced natural logged transformations of them $\mathtt{DLnmcdose_t}$ and $\mathtt{DLnfcdose_t}$, these variables had to be dropped from the model because they precluding convergence of the equations. We also endeavored to include in these equations exogenous variables that may be significantly related to the outcome measure–such as, a self-report of the number of illnesses–namely, $\mathtt{femillct_t}$ or $\mathtt{maleillct_t}$, or a rescaled version of the perceived risk of exposure to radiation –namely, $\mathtt{frpre_t}$ or $\mathtt{mrpre_t}$. If any of these variables is not significantly related to the outcome variable or precludes model convergence, the problematic variable is pruned from the final model. The components of the state vector in the 2010 state for the male and female models are presented in the anxiety equations, consisting of a local level, explanatory regressors, intervention impact indicators, and and irregular component (the error). A more complete description of parameter estimates of the components of the final state vector at 2010 are displayed in Table 3.

$$\begin{aligned} FemaleAnxiety_{t+1} = 0.104Level_t + 2.312LS1986 + .031LS1997 \\ +.036LS2007 + 0.040Outlier2008 \\ +0.041Outlier2009 - 1.398frpre_t + e_t \end{aligned} \tag{23}$$

$$\begin{aligned} MaleAnxiety_{t+1} = -0.017Level_t + 4.019LS1986 + 0.040LS2004 \\ +0.047LS2008 + 0.260maleillct_t - 3.096mrpre_t + e_t \end{aligned} \tag{24}$$

where the subscript t indicates a time varying process and LS signifies a level shift impact of events at a point in time. More specifically, $\mathtt{Level_t}$ = a time varying (local) level, `LS1986` = the impact of Chornobyl on a level shift in anxiety, `LS1991` = level shift impact of events in 1991 on anxiety, `LS2004`= the impact of events in 2004 on the level shift of anxiety, `LS2008` = the impact of events in 2008 on a level shift in anxiety, `femillct` = the time varying female count of illness, $\mathtt{maleillct_t}$ = the time-varying male count of illness, and $\texttt{frpre}_{\texttt{t}}$= the time varying female rescaled percievied risk of exposure, and $\texttt{mrpre}_{\texttt{t}}$ = the time varying male rescaled perceived risk of exposure. In this formula, a time varying local level is a time varying mean of the anxiety process.

The negative sign in front of male and female rescaled perceived risk of exposure need not mean that there is a negative relationship throughout the process between the perceived risk and anxiety. Rather, in the last state (2010) when these components are being assessed, this appears to have been so because at that time there is a decline in the level of the psychological sequelae but not by the level of the perceived risk.

The male and female models both fit the data very well. Figures 7 and 7 display the model fit for both the female and male anxiety models. Indeed both male and female models exhibit high R^2 and low prediction error variances. Both models exhibit a sharp spike in anxiety in 1986 at the time of the Chornobyl disaster and a more or less exponential decline thereafter. However, neither the male nor the female anxiety level return to a pre-1986 level. Instead, they appear to drift upward, with a slight rise in 2008 at the onset of the great global recession and with a slight decline in 2010 for females. The parameter estimates for the components of the state vector in the final state are displayed in Table 3.

To confirm statistical validity of the models we examine the residual homogeneity, normality, and stability. In Figures 8 and 9, we note that the the standardized residuals are generally well behaved with the exception of a possible negative end-effect in 2010 for women. The correlograms for the autocorrelation functions are generally well-behaved with a possible significance of a negative third lag in the autocorrelation function not posing much of a problem. Residual normality is not a problem as suggested by Bowman-Shenton tests. Nor do the cusum t-tests suggest a problem with the residuals.

An examination of the auxiliary residuals reported in Table 3 reveals no residual problem with irregular or level outliers. It would appear that the model is not improperly modeled.

Table 3: Final 2010 state space Anxiety models for males and Females

Female Anxiety Model				
$R^2 = 0.988$				
Prediction error variance = 0.00015				
Schwartz Criterion= -7.933				
	Coefficient	**RMSE**	**T-value**	**p-value**
Local Level at 2010	0.104	0.026	4.05	0.000
1986 Level break	2.312	0.183	12.616	0.000
1997 Level break	0.031	0.013	2.325	0.029
2007 Level break	0.036	0.014	2.646	0.014
2008 outlier	0.039	0.012	3.211	0.004
2009 outlier	.041	.0122	3.307	0.003
female rescaled perceived risk	-1.398	.125	-11.153	0.000
Male Anxiety model				
$R^2 = 0.971$				
Prediction error variance = 0.0002				
Schwartz criterion= - 7.687				
	Coefficient	**RMSE**	**T-value**	**p-value**
Local Level at 2010	-0.017			0.621
1986 level break	4.019	0.479	8.385	0.000
2004 level break	0.040	0.015	2.495	0.011
2008 level break	0.046	0.015	3.165	0.004
male rescaled perceived risk	-3.096	0.395	-7.847	0.000
male count of self-reported illnesses	0.260	0.034	3.100	0.005

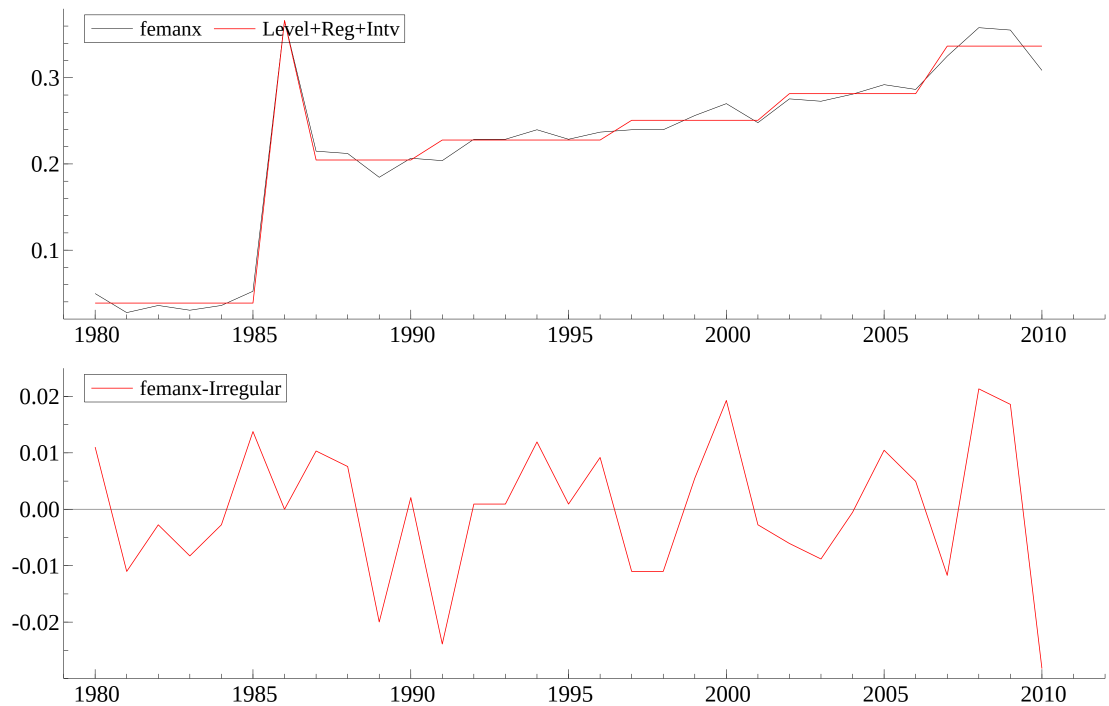

Figure 7: Female anxiety model

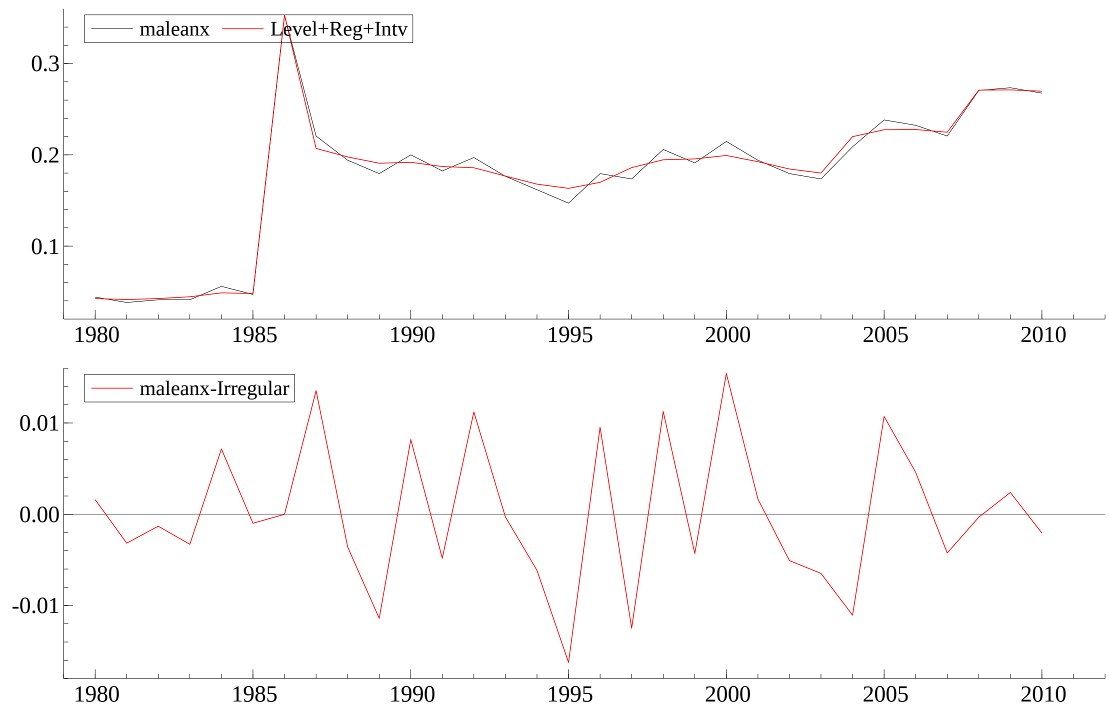

Figure 8: Male anxiety model

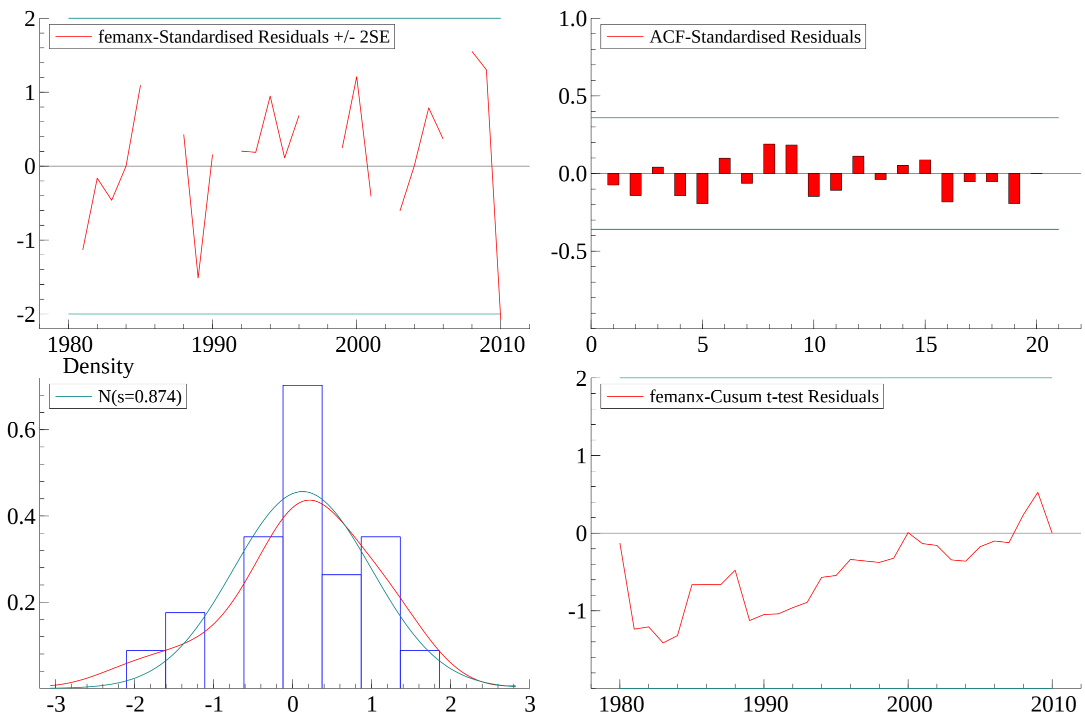

Figure 9: Residual Analysis of Final Female Anxiety Model

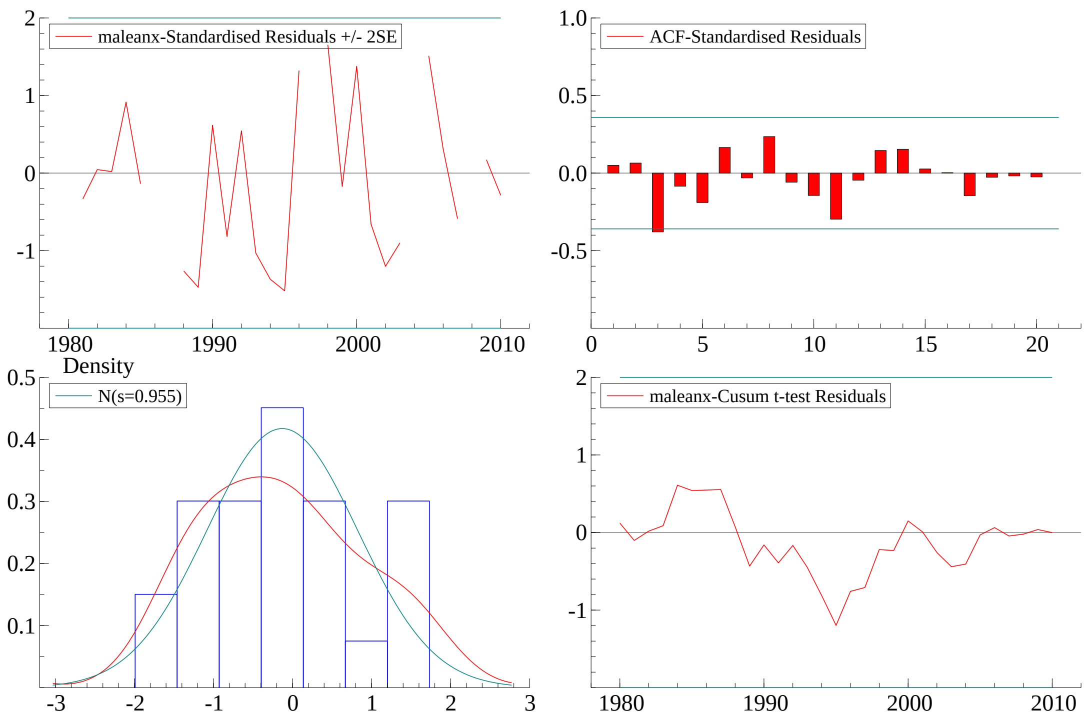

Figure 10: Residual Analysis of Final Male Anxiety Model

Table 4: Anxiety models auxiliary residual analysis for outlier and level breaks

	Irregular Intervention t-test	**Level shift t-test**
Female model	only end-effect in 2010	only end-effect in 2010
Male model	no significant residuals.	no significant residuals

To guard against overfitting a model, we assess the predictive validity of the depression models over a validation subsample of the last several observations. We observe no significant differences between the signal and the data with the possible exceptions of some end-effects, in 2010, which may be difficult to fit insofar as filtering adjustments are usually done with a time lag of one period. The Chow and cusum t-tests provide assessments of predictive failure if they yield significant results. The variation in this subsample size arises from the presence of outlier or level shift indicators within the time horizon of the subsample, as from the test results in Table 5.

Table 5: Predictive validation tests for the anxiety models

Post-sample predictive tests:	coefficient	p-value
Female model		
Failure Chi2(7) test	10.539	[0.160]
cusum t(7) test	0.682	[0.517]
Male model		
Failure Chi2(8) test	12.539	[0.129]
cusum t(8) test	1.902	[0.094]

6.3 Depression Models

When we model the depression responses to the Chornobyl and related events for males and females, we obtain the parameter estimates contained in Table 6. The equations developed by the model are contained in Equations 25 and 26. The model parameter estimates are displayed in the this Table 6. The fit of these models is displayed in Figures 11 and 12 . Nevertheless, we have to examine the model residuals to assure ourselves of their statistical congruency with their underlying assumptions. In Figures 13 and 14, we display the standardized residuals, the correlogram, the residual normality and the cusum t-test residuals. In Table 7, we list remaining auxiliary residual issues.

$$\begin{aligned} FemaleDepression_{t+1} = 0.143Level_t + .967LS1986 + 0.077LS2008 \\ +0.054Outlier2009 - 0.557frpre_t + e_t \end{aligned} \tag{25}$$

$$\begin{aligned} MaleDepression_{t+1} = 0.105Level_t + 1.051LS1986 - 0.032LS1991 \\ +0.032LS1996 + 0.019LS2008 + \\ +0.019Outlier2009 - 0.724mrpre_t + e_t \end{aligned} \tag{26}$$

Table 6: Final 2010 state space Depression models for males and Females

Female Depression Model				
$R^2 = 0.952$				
Prediction error variance = 0.000533				
Schwartz Criterion= -6.873				
	Coefficient	**RMSE**	**T-value**	**p-value**
Level at 2010	0.143	0.043	3.333	[0.003]
1986 Level break	0.967	0.328	2.950	[0.007]
2008 Level break	0.077	0.025	3.103	[0.005]
2009 Outlier	0.054	0.020	2.672	[0.013]
female rescaled perceived risk	-0.557	0.226	-2.469	[0.020]
Male Depression model				
$R^2 = 0.989$				
Prediction error variance = 6.0563e-050				
Schwartz criterion= -8.826				
	Coefficient	**RMSE**	**T-value**	**p-value**
Level at 2010	0.105	0.0205	5.088	[0.0003]
1986 level break	1.051	0.166	6.307	[0.000]
1991 level break	-0.032	0.009	-3.122	[0.001]
1996 level break	0.032	0.009	3.660	[0.001]
2008 level break	0.026	0.009	2.993	[0.006]
Outlier 2009	0.019	0.006	3.057	[0.005]
male rescaled perceived risk	-0.724	0.139	-5.221	[0.000]

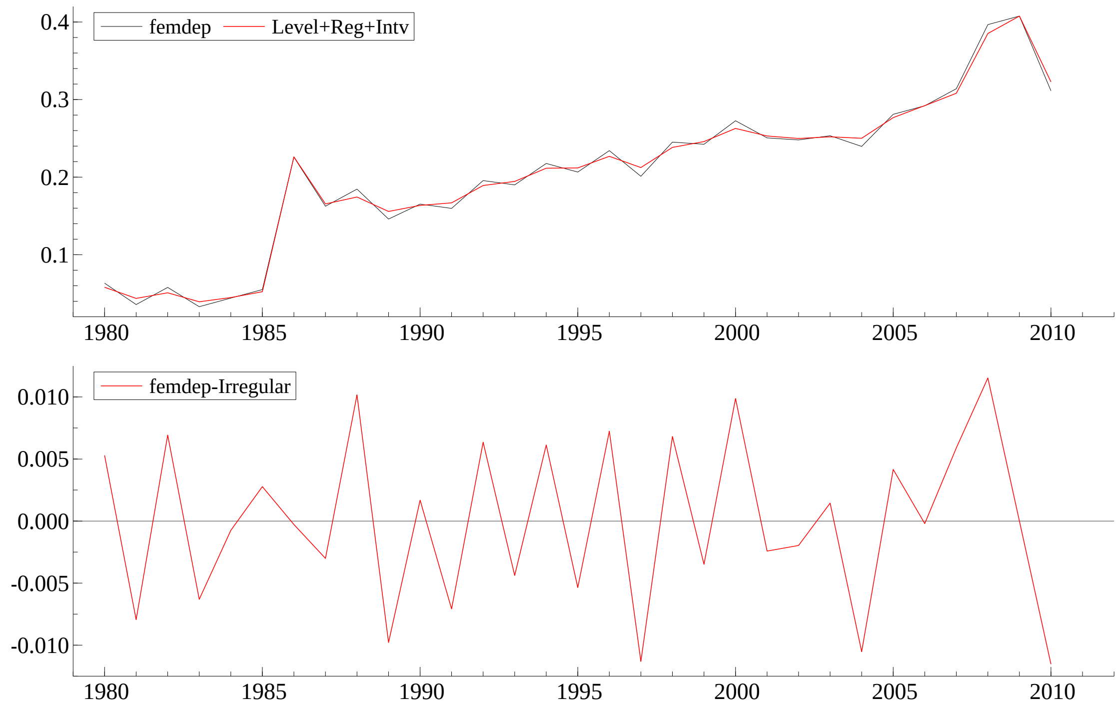

Figure 11: Female Depression signal and data

Figures 11 and 12 respectively display the female and male fit of the signals comprising the combined components. From Figure 11, we can see that the generated signal tracks the data nicely. In both models, the standardized residuals resided within $\pm$ 2 standard errors. There was no problematic residual serial correlation either. Parameter stability was confirmed by the cusum t-tests remaining well behaved also. In both models, residual normality was maintained as well. In general, the model fit the data very well.

A diagnosis of the residuals indicates how well the model assumptions are fulfilled. Diagnosis of the female depression model assumption fulfillment is based on Figure 13 while diagnosis of the male model assumption fulfillment can be done from Figure 14. The female depression model residuals are very well-behaved. They have no standardized residuals exceeding the 2 standard error bounds. There is no residual serial correlation exceeding the bounds of significance. The residuals do not appear to be statistically significantly non-normal and there appears to be no female depression residual with a significant cusum t-test.

Although the male depression model appears to fit the data exceptionally well (so much so that the residual fit graph is not displayed), the residuals do appear to be slightly less normally distributed. Also in several instances, the male depression standardized residuals appear to border on statistical significance. However, only end effects in the overall model appear to be capable of posing any problem and that might be one of forecasting rather than fitting.

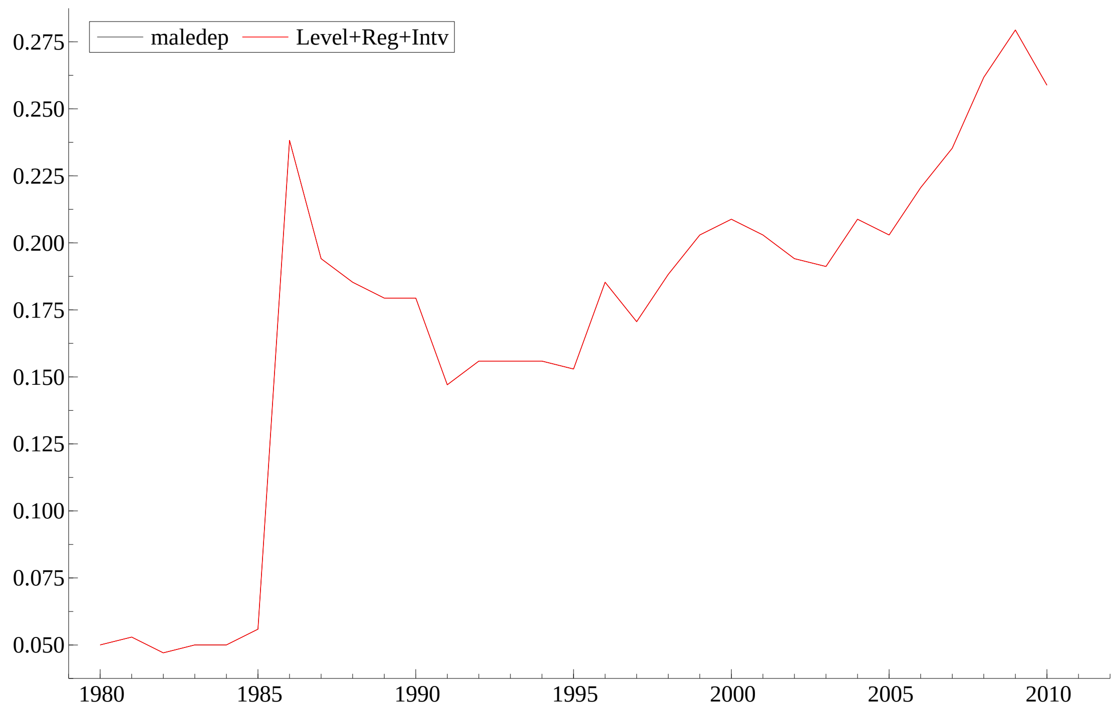

Figure 12: Male Depression signal and data

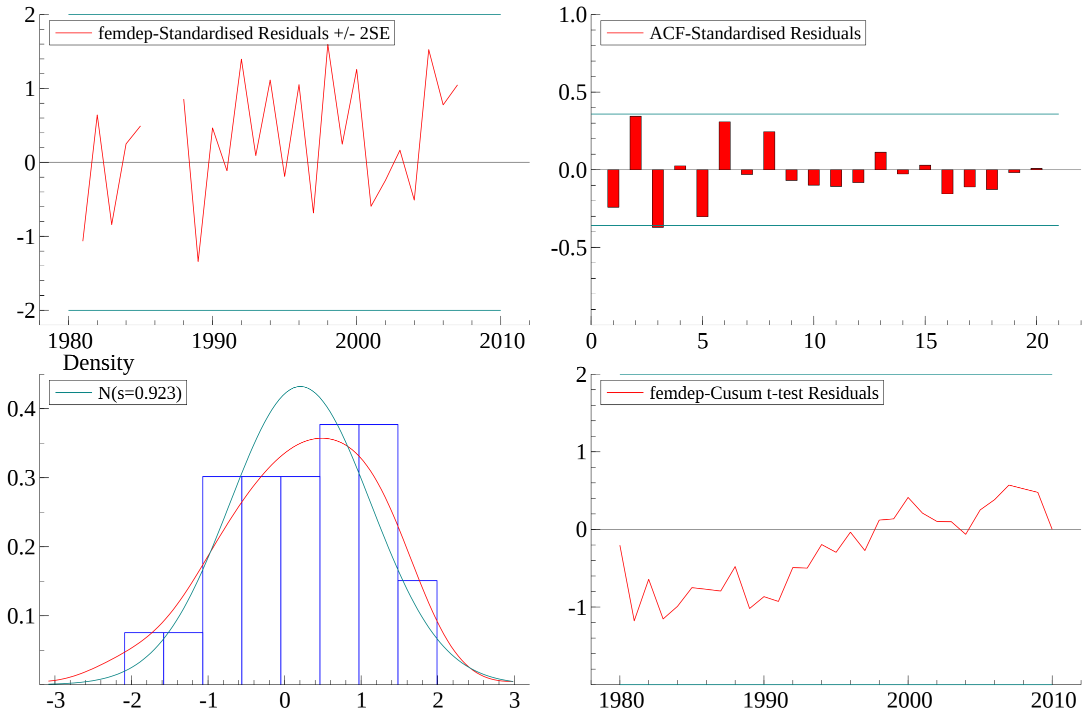

Figure 13: Female depression model residuals

Table 7: Depression models auxiliary residual analysis for outlier and level breaks

	Irregular Intervention t-test	**Level shift t-test**
Female model	no significant unmodeled outliers	no significant unmodeled level shifts
Male model	end-effects at 2008-2010	only end-effect at 2009 and 2010

However, both male and female models pass the predictive failure Chow and cusum t-tests in that neither model yields a significant result for the test of the significance of the residuals within this time horizon, as shown in Table 8. Therefore, concerns about end-effects may have been without realization.

Apart from some end effects, these models fit the data very well and appear to pose no problem for a post-sample forecast evaluation. We now turn to the PTSD models.

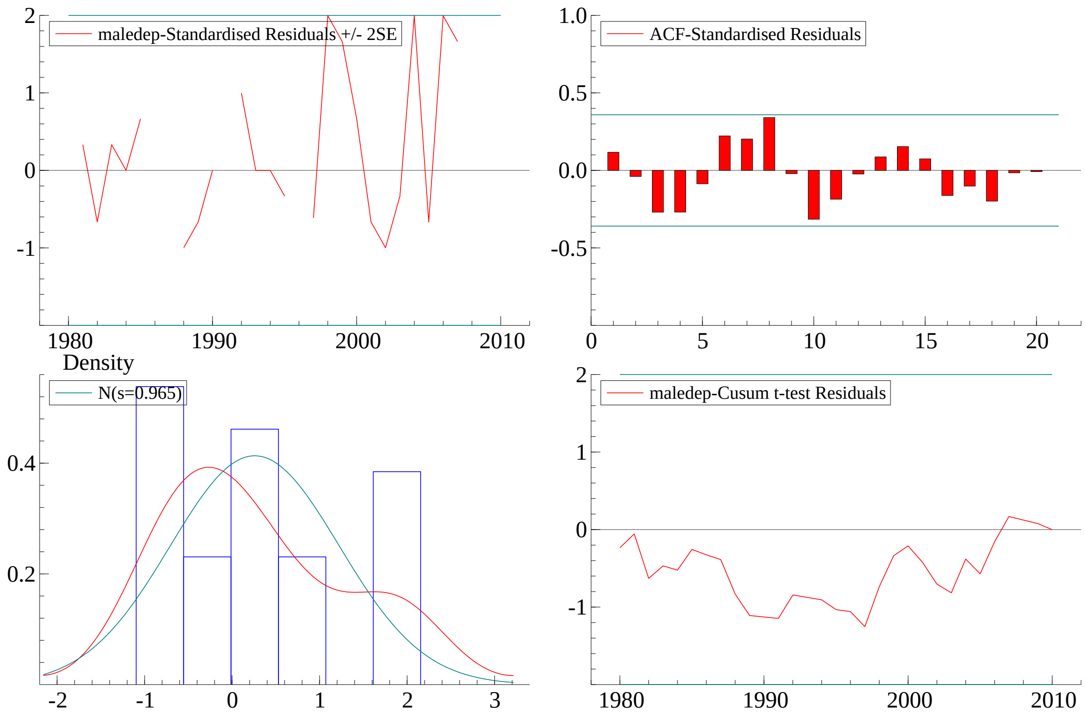

Figure 14: Male depression model residuals

Table 8: Predictive validation tests for the Depression models

Post-sample predictive tests:	coefficient	p-value
Female model		
Failure Chi2(6) test	11.2662	[0.081]
cusum t(6) test	0.1516	[0.885]
Male model		
Failure Chi2(6) test	11.335	[0.079]
cusum t(6) test	1.805	[0.121]

6.4 PTSD Models

The formulae for the PTSD models for women and men are given respectively in Equations 27 and 28. Both models consist of time-varying (local) levels plus explanatory variables for the self-reported gender-specific count of illnesses as well as gender-specific perceived risk of exposure to Chornobyl radiation. The last two variables are time varying. However, the model is also defined by several level shifts are particular periods of time, the most prominent of which is usually that at the time of Chornobyl (1986). The female PTSD exhibits a rise in level of PTSD in 2008 and another peak in 2009, both of which were at about the time of the great global recession and the dispute with Russia over the flow of gas to the Ukraine. Male PTSD in contrast exhibits a reduction in the level in 1988, more than a year after Chornobyl, and subsequent level shift upwards in 2000, 2004, and in 2008. With PTSD other earlier factors may be at work here. This remains an area for future research.

The fit of both models is very good with model R^2 both in the mid to high 0.90 region. As can be observed in Table 9, the prediction error variance for both models is very small. The structural effects on current PTSD level according to this model are a time-varying level component that is almost significant (with an n=31), several interventions and the remaining irregular variation over time. The equations below represent the components in the state vector at the final state (2010).

$$\begin{aligned} FemalePTSD_{t+1} = 0.007Level_t + 3.282LS1986 + 0.073Outlier2008 \\ +0.065Outlier2009 + 0.124femillct_t - 2.131frpre_t + e_t \end{aligned} \tag{27}$$

$$\begin{aligned} MalePTSD_{t+1} = -0.032Level_t + 4.993LS1986 - 0.025LS1988 \\ +0.021LS2000 + 0.027LS2004 + \\ +0.018Outlier2008 + 0.237millct_t - 3.941mrpre_t + e_t \end{aligned} \tag{28}$$

The model fit for the PTSD models can be observed in Figures 15 and 16. The model fit tracks the data nicely in both cases.

Both models appear to fulfill their model assumptions well. Neither model exhibits troublesome residuals. The standardized residuals of the PTSD models are very well behaved, as shown in Figure 17 and Figure 18. The stability of the model is supported by the non-significance of the cumsum t-tests for the residuals, and the normality of the models does not appear to be seriously impaired as shown in both of the histograms with superimposed kernel density graphs for the actual and theoretical normal distribution.

The auxiliary residuals indicate the proper fitting of regime indicators, as shown in Table 10. The auxiliary residuals of the PTSD models indicate that the models are generally well modeled regarding outliers and level shifts.

In order to guard against overfitting a model, we assess the predictive validity of the PTSD models over a validation subsample of the last several observations.

Table 9: Final 2010 state space PTSD models at 2010 for males and Females

Female PTSD Model				
$R^2 = 0.941$				
Prediction error variance = 0.00015				
Schwartz Criterion= -8.040				
	Coefficient	**RMSE**	**T-value**	**p-value**
Local Level at 2010	-0.007			[0.750]
Level break 1986(1)	3.282	0.245	13.375	[0.000]
Outlier 2008(1)	0.075	0.013	5.944	[0.000]
Outlier 2009(1)	0.065	0.013	5.034	[0.000]
female count of illness	0.124	0.043	2.882	[0.008]
female rescaled perceived risk	-2.131	0.167	-12.745	[0.000]
Male PTSD model				
$R^2 = 0.987$				
Prediction error variance = 0.0000522				
Schwartz criterion= -8.857				
	Coefficient	**RMSE**	**T-value**	**p-value**
Local Level at 2010	-0.0143			[0.373]
Level break 1986(1)	4.993	0.305	16.448	[0.000]
Level break 1988(1)	-0.028	0.009	-3.269	[0.004]
Level break 2000(1)	0.023	0.007	3.110	[0.005]
Level break 2002(1)	-0.020	0.008	- 2.559	[0.018]
Level break 2004(1)	0.027	0.009	3.139	[0.005]
Outlier 2008(1)	0.018	0.008	4.221	[0.000]
male rescaled perceived risk	-3.914	0.227	-17.269	[0.000]
male illness count	0.227	0.041	5.579	[0.000]

Table 10: PTSD models auxiliary residual analysis for outlier and level breaks

	Irregular Intervention t-test	**Level shift t-test**
Female model	no significant outliers	no significant level shifts
Male model	no significant outliers	no significant level shifts

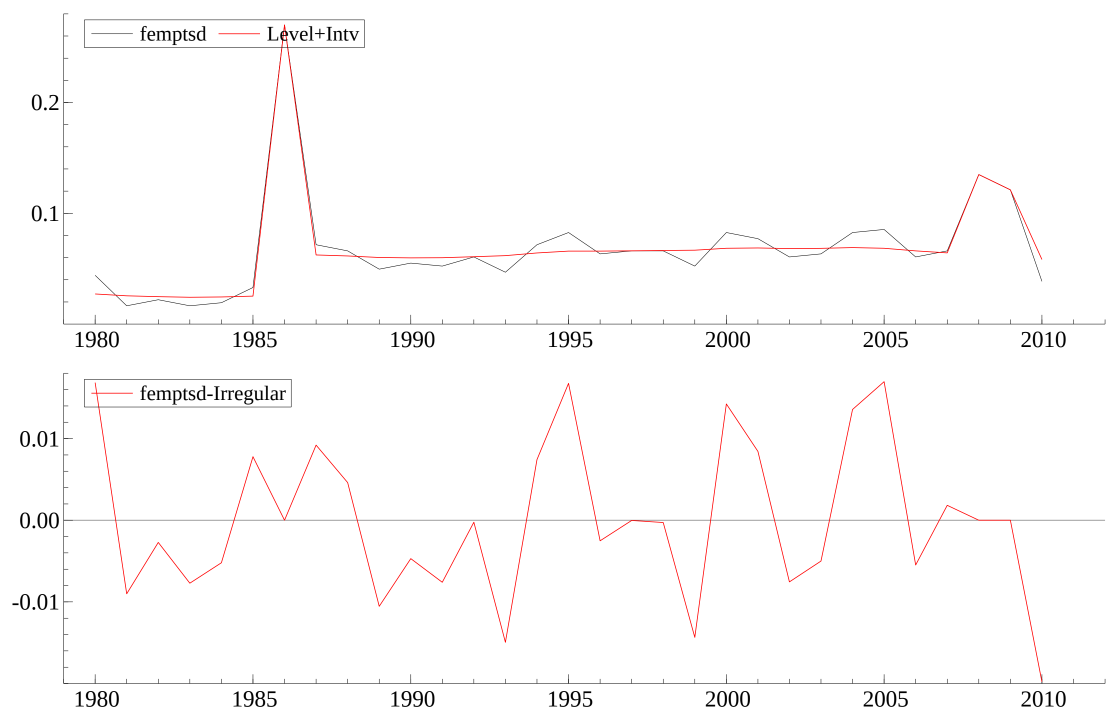

Figure 15: Female PTSD model fit

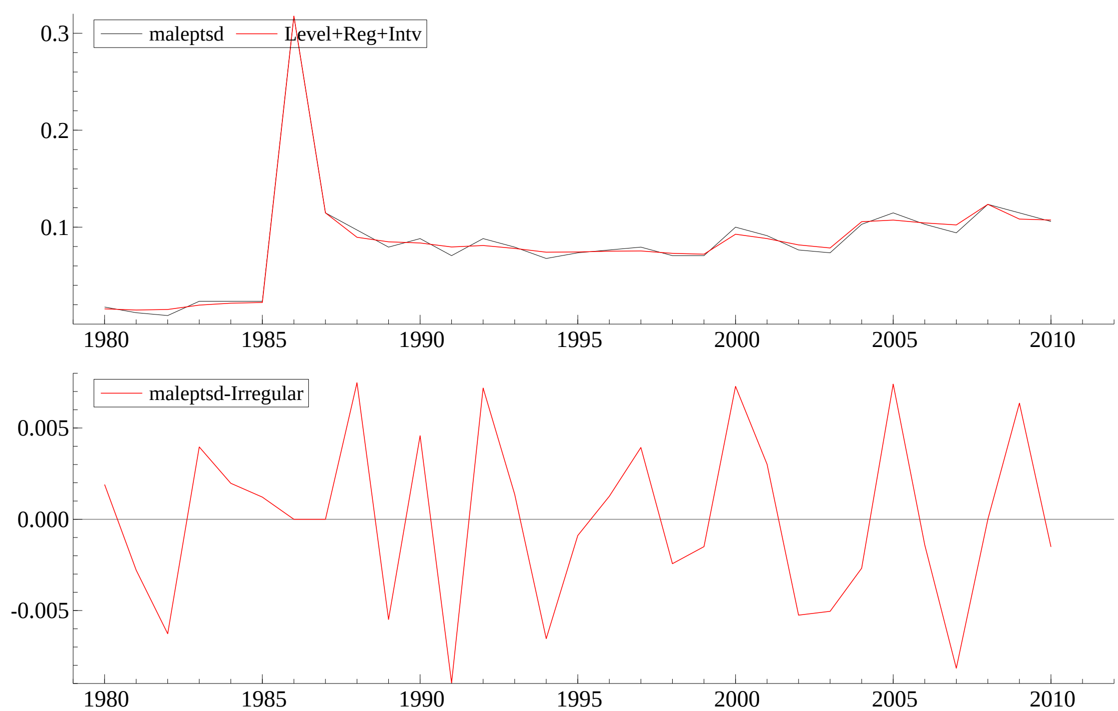

Figure 16: Male PTSD model fit

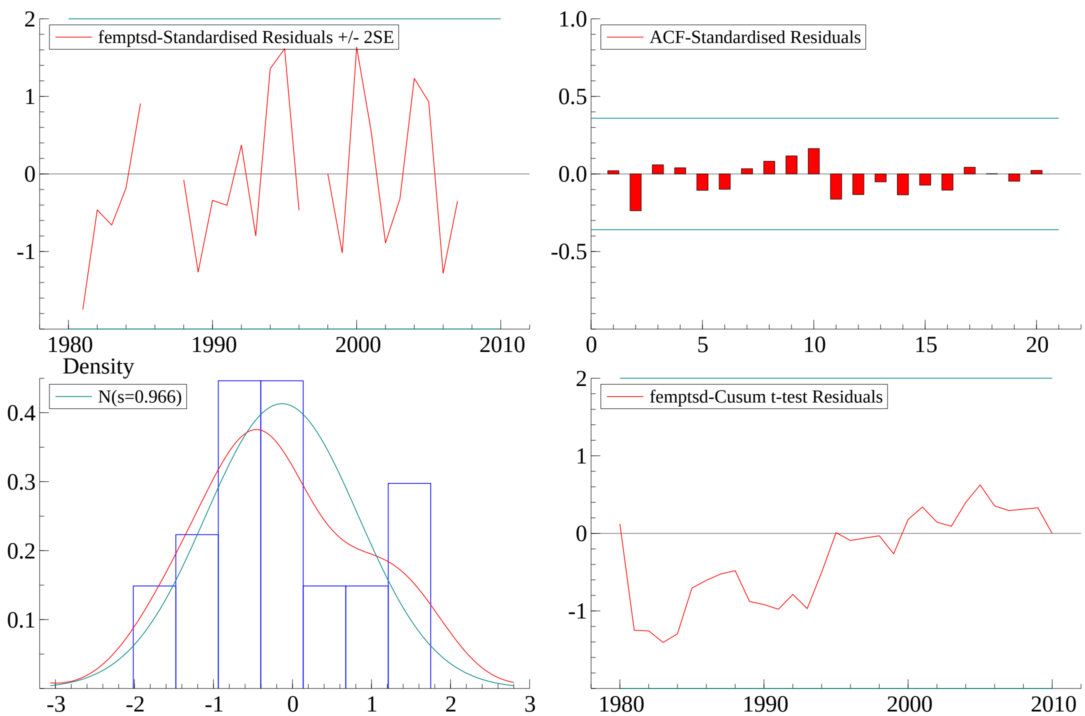

Figure 17: Female PTSD model residuals

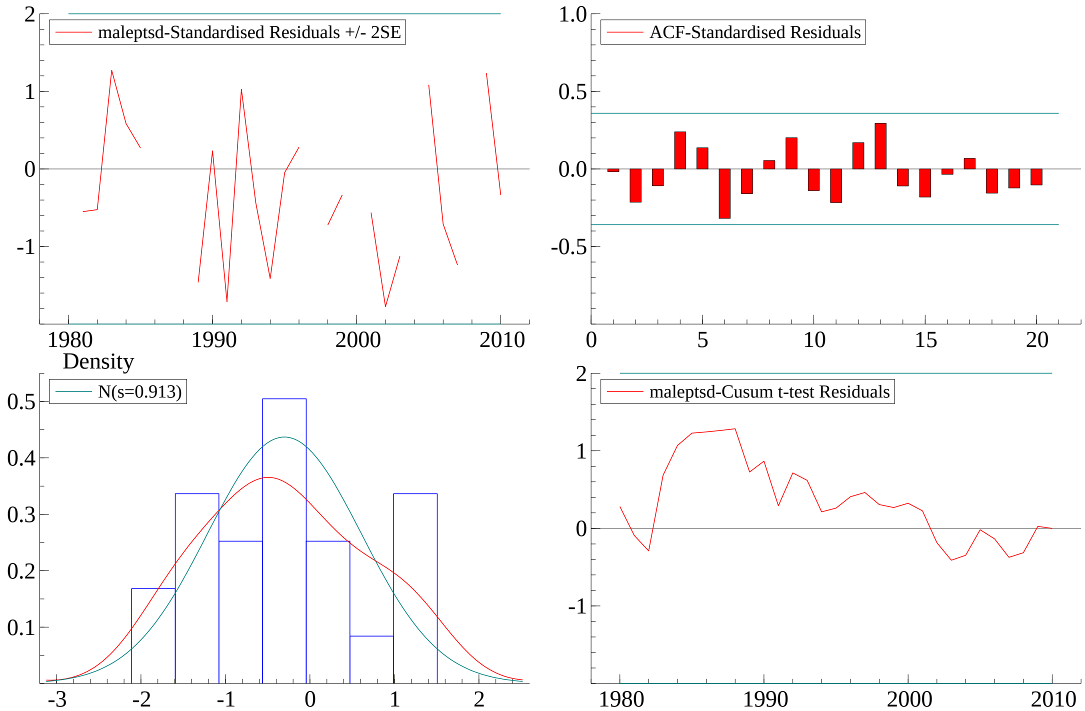

Figure 18: Male PTSD model residuals

Table 11: Predictive validation tests for the PTSD models

Post-sample predictive tests:	coefficient	p-value
Female model		
Failure Chi2(6) test	7.994	[0.239]
cusum t(6) test	-0.703	[1.492]
Male model		
Failure Chi2(6) test	6.059	[0.417]
cusum t(6) test	-0.021	[1.016]

To do so, we endeavor to ascertain whether there are significant differences between the signal and the data. The Chow and cusum t-tests provide assessments of predictive failure if they yield significant results. The nonsignificant results indicate that there is not a statistically significant difference between the signal and the data, as shown in Table 11.

7 Diagnostic validation

To show that there may be validity between retrospective self-reports and established diagnostic scales, we use a clustered robust path analysis. Some of these measures may be predicted by simple unidirectional paths as is the case with Female depression, shown in Figure 19. In other situations, self-reports from multiple waves are related to the standard diagnostic scales we use for our analysis. For example, Figure 20 depicts significant paths extending from self-reports in all three waves to male respondent scores on the revised Mississippi Chornobyl scale. Therefore, we not only examine direct paths from self-reports to the these diagnostic scales, we also examine total effects path coefficients to reveal the relationship between the self-reports and the diagnostic scales.

Table 12 lists the standardized direct path coefficients tested with clustered robust standard errors to control for the autocorrelation between observations. The established scales used are the Brief symptom inventory measures for anxiety and depression along with the revised civilian Mississippi PTSD scale for PTSD from Chornobyl. Applying a robust path analysis to adjust for autocorrelation among waves of our data, we are able to consider both the standardized direct and total effect path coefficients. By considering the direct and total effects between the self-reports and the diagnostic scales, we entertain a more comprehensive perspective about the nature of the relationships than we would had we merely considered the direct effects. The total effects will include the direct plus the indirect effects contributed by intervening variables.

The parameter estimates of the direct path effects displayed in Table 12 reveal significant direct relationships between the self-reports in the most recent wave 3 and the diagnostic tests for anxiety among males and females, for de-

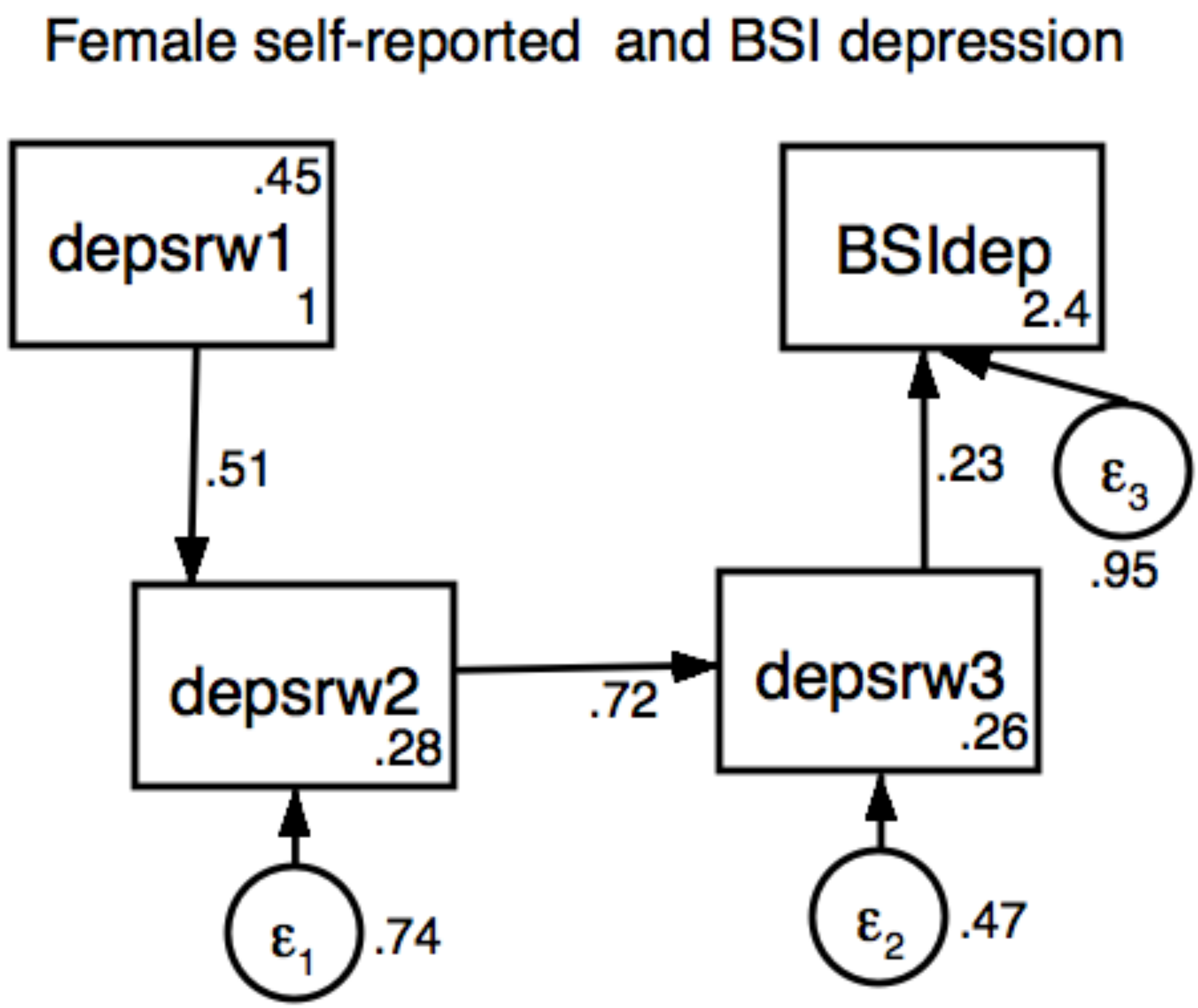

Figure 19: Female Depression paths between self-reports and BSI depression scale

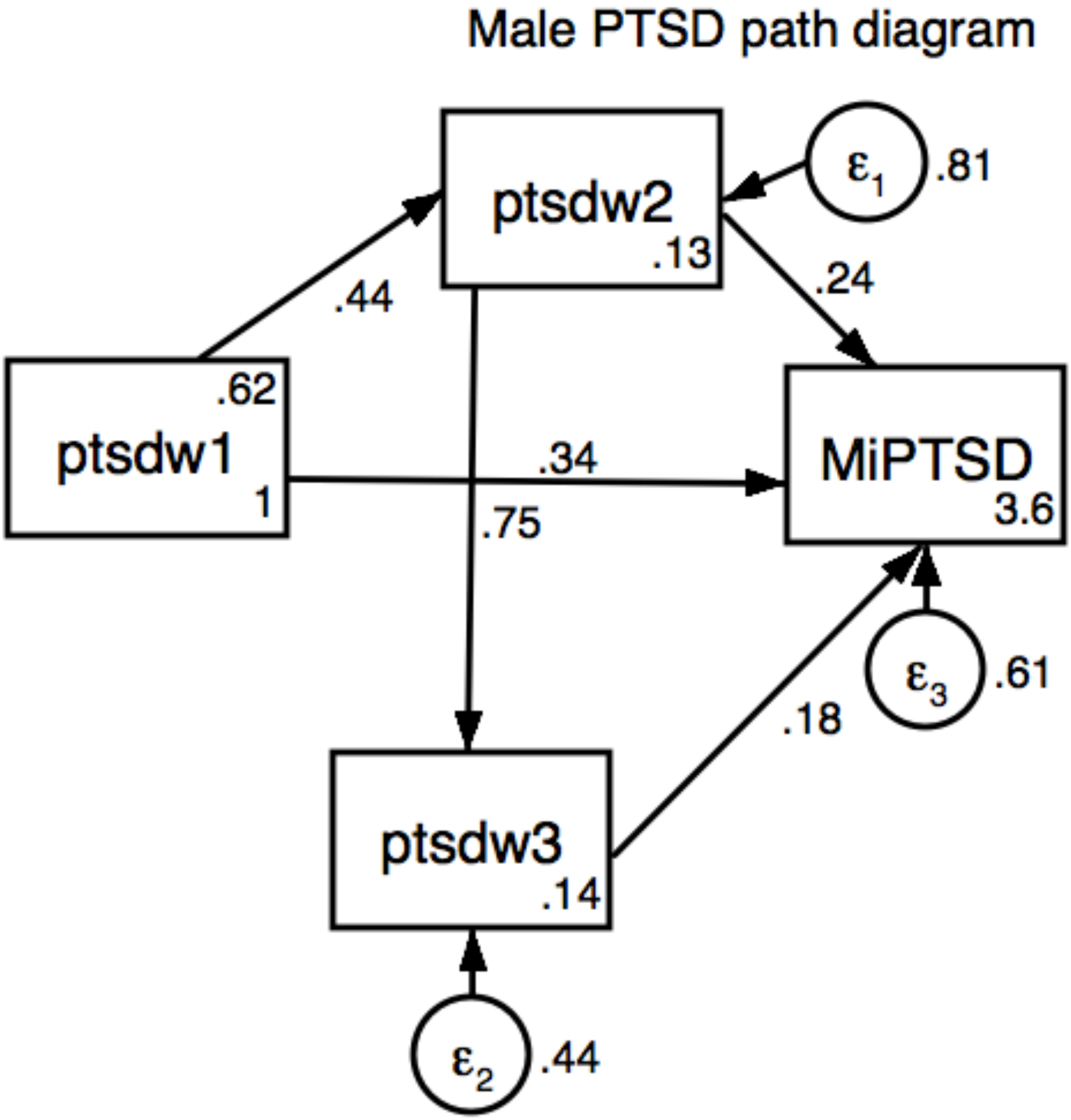

Figure 20: Male PTSD paths between self-reports and civilian revised Mississippi PTSD scale

pression among females and males, and for PTSD among males and females. The direct path coefficient between earlier waves and the diagnostic test are also shown to be significant in anxiety in males and females, and for PTSD for males and females. This is indeed the case wherever there is a path except for females in wave 2.

If we consider the total effects shown in Table 13, we can see that in all cases, the total effect path coefficients are found to be significantly related to the standard diagnostic scale. For male and female anxiety, and for male PTSD, we observe that the standardized total path coefficients decline in magnitude over time. This could be due to the initial threat and surprise and lack of time to prepare. Over time, many people may recognize that it is likely that the actual threat to them was not as pronounced as they first thought and they have learned to cope with the situation. But this pattern does not seem to hold with regard to depression. For both males and females, those who were depressed appear in general to have become more depressed on the average than they were at first if we consider the magnitude of the total standardized path coefficients an indicator of unresolved issues.

Each of the above models were fit with conventional standard errors before applying clustered-robust standard errors. The latter are generally larger than the former type of errors and the following table shows the Likelihood ratio test of the model vs that of the saturated model. The test is distributed as a χ^2 with 1 degree of freedom. The results are contained in Table 14.

If we wonder about the internal consistency between the wave 3 self-report and the diagnostic scale, we can examine the standardized alpha reliability coefficient between the two of them. We find substantial, if not always high, internal consistency, as shown in Table 15. We focus on wave 3 rather than all waves because the wave 3 score be closest to the diagnostic scale result obtained. If the internal consistencies are not as high as suspected, this may be evidence of population resilience over time to the initial impact.

8 Recapitulation of time series analysis of anxiety, depression, and PTSD

In this short paper, we have endeavored to show how different time series models can be used to quantify psychological sequelae of a nuclear incident. Although we have emphasized impact analysis of events and level shifts, we have been able to quantify the relationships. The models developed provide an approach for post-sample forecasting evaluation of the techniques applied to psychological sequelae after a nuclear incident. However, we do find that driving the models of anxiety, depression, and PTSD is a perceived risk of exposure. Moreover, to some extent anxiety and PTSD models are also empirically based on male and female self-reported frequencies of illnesses observed. These may be important empirical findings in understanding the psychological dysfunctionality that follows a nuclear incident. These would be factors that societies confronting such

Table 12: Standardized Direct Effect path coefficients from self-reports to Diagnostic instrument

Model	**Gender**	**Wave of source**	**Diagnostic instrument**	**coefficient**	**clustered robust standard error**	**z**	**p-value**
Anxiety	female	1	BSIanx	0.250	0.006	4.05	0.000
Anxiety	female	2	BSIanx	-	-	-	-
Anxiety	female	3	BSIanx	0.313	0.006	5.12	0.000
Anxiety	male	1	BSIanx	0.151	0.005	2.37	0.018
Anxiety	male	2	BSIanx	-		-	-
Anxiety	male	3	BSIanx	0.203	0.012	2.53	0.011
Depression	female	1	BSIdep	-	-	-	-
Depression	female	2	BSIdep	-	-	-	-
Depression	female	3	BSIdep	0.234	0.009	4.56	0.000
Depression	male	1	BSIdep	-	-	-	-
Depression	male	2	BSIdep	-	-	-	-
Depression	male	3	BSIdep	0.286	0.012	3.77	0.000
PTSD	female	1	MiPTSD	0.181	0.021	3.12	0.002
PTSD	female	2	MiPTSD	0.023	0.101	0.34	0.738
PTSD	female	3	MiPTSD	0.372	0.090	5.87	0.000
PTSD	male	1	MiPTSD	0.344	0.018	5.88	0.000
PTSD	male	2	MiPTSD	0.240	0.073	3.10	0.002
PTSD	male	3	MiPTSD	0.179	0.018	2.37	0.018
- = no path							

Table 13: Standardized Total Effects from self-reports to Diagnostic instrument

Model	**Gender**	**Wave of source**	**Diagnostic instrument**	**coefficient**	**clustered robust standard error**	**z**	**p-value**
Anxiety	female	1	BSIanx	0.364	0.006	6.41	0.000
Anxiety	female	2	BSIanx	0.246	0.002	18.47	0.000
Anxiety	female	3	BSIanx	0.312	0.010	5.12	0.000
Anxiety	male	1	BSIanx	0.228	0.004	3.93	0.000
Anxiety	male	2	BSIanx	0.141	0.002	9.88	0.000
Anxiety	male	3	BSIanx	0.203	0.012	2.53	0.011
Depression	female	1	BSIdep	0.086	0.003	4.06	0.000
Depression	female	2	BSIdep	0.170	0.002	14.90	0.000
Depression	female	3	BSIdep	0.234	0.009	4.56	0.000
Depression	male	1	BSIdep	0.095	0.002	3.75	0.000
Depression	male	2	BSIdep	0.203	0.004	9.78	0.000
Depression	male	3	BSIdep	0.286	.012	3.77	0.000
PTSD	female	1	MiPTSD	0.238	0.021	4.12	0.000
PTSD	female	2	MiPTSD	0.212	0.118	2.62	0.009
PTSD	female	3	MiPTSD	0.372	0.090	5.87	0.000
PTSD	male	1	MiPTSD	0.508	0.018	8.86	0.000
PTSD	male	2	MiPTSD	0.374	0.065	5.46	0.000
PTSD	male	3	MiPTSD	0.179	0.075	2.37	0.018

Table 14: Likelihood ratio test of Path Model vs saturated model

Model	**Gender**	**Model LR** χ^2 *with* $df(1)$	**p-value**
Anxiety	female	1.02	0.312
Anxiety	male	0.59	0.443
Depression	female	2.62	0.455
Depression	male	5.16	0.160
PTSD	female	1.11	0.293
PTSD	male	0.67	0.412

Table 15: Standardized alpha reliabilities between wave 3 self-report and diagnostic scale

Model	**Gender**	**Standardized alpha**
Anxiety	female	0.569
Anxiety	male	0.413
Depression	female	0.380
Depression	male	0.445
PTSD	female	0.573
PTSD	male	0.632

problems must prepare to deal with and treat.How this can be done may be a direction for future research.

It should be noted that there is a growth in anxiety and depression on the part of females and males revealed in Figures 1, 3, and 4 beginning in 2004 and becoming more pronounced in 2008 and 2009. These may be due to other factors influencing these psychological issues at the time. Among the many that could have contributed to these rises is anxiety and depression, and to a lesser extent, PTSD, are the Orange Revolution in 2004, which came about as a result of protests against electoral fraud in the election of 2004, a short gas crisis in January 2006, which lasted four days. The Great Global Recession which began in September-October 2008 engendered a global decline in the demand and a general slowdown in economic production [29, 13-14]. On January 2009, Russia cut off all gas to the Ukraine. A week later deliveries to Europe were also shut off. Many companies stopped operations because of lack of gas. The domestic and export industries greatly suffered. It was not till 20 January that this matter was resolved so that gas began to flow again to Europe and the Ukraine. This situation, along with other relevant factors, may have led to a rational increase of anxiety and depression at the time.

9 Directions for future research

Although we are able to track the development of these psychological sequelae, we may not have all of the sources contributing to them in our model. That may be an area for future research. For example, with the PTSD models, there may be persistent factors at work that are not included as explanatory variables. In a long-term retrospective longitudinal study, we may have all of the factors modeled to explain very recent spikes in the psychological sequelae. However, we may be able to point to some avenues for future research in such models. Nonetheless, the method we apply may be useful in understanding change points in the development of the sense of well-being and psychological functionality of a society.

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