A Time Series Analysis of Anxiety, Depression, and PTSD among Ukrainian residents after Chornobyl

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1) Robert Alan Yaffee 2) RoseMarie Perez Foster
3) Thomas B. Borak 3) Remi J. Frazier
4) Mariya Burdina 5) Victor Chtenguelov
and 6) Gleb Prib

Affiliations:

1) Silver School of Social Work, New York University, New York, New York
2) Natural Hazards Center, University of Colorado at Boulder
3) Environmental and Radiological Health Sciences,
Colorado State University, Fort Collins, Colorado
4) Department of Economics and International Business,
University of Central Oklahoma, Edmond, Oklahoma
5) Deputy Director, Ukrainian Institute on Public Health Policy , Kiev, Ukraine
6) Applied Psychology, Academy of Labor and Social Relations, Kiev, Ukraine

Contents

List of Tables

List of Figures

1 Acknowledgements

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2 Introduction

2.0.1 The area surveyed

In this analysis, we investigate longitudinal patterns of anxiety, depression, and PTSD following the Chornobyl nuclear incident among residents of the area. The survey respondents lived in either Kiev or Zhitomyr Oblasts. The Chornobyl nuclear plant was located near Pripyat in the Oblast of Kiev and Zhitomyr was the adjacent Oblast to its west. Respondents were selected from a random generation of phone numbers which were attached to the area codes for the raions and cities in both the Kiev and Zhitomyr Oblasts provided by the Ukrainian telephone company. Approximately 14% of the randomly generated numbers were actual phone numbers assigned. Respondents who failed to answer at first were given up to four call backs before the number was discarded and the next one tried. Willing respondents were paid a nominal sum for their time after an interview was completed at their home at a mutually convenient time. Only those who agreed voluntarily were interviewed.

The data were recorded on laptop computers and, after an independent auditing group confirmed that the responses were completely voluntary and offered with the consent of the respondents, was the data uploaded to the Vovici company whose personnel input the data into a computer file.

2.0.2 Hypotheses under consideration

In this analysis, we analyze subject matter included in hypotheses 3, 4, 5, and 6. We do not test those hypotheses per se, but we open up a longitudinal dimension in their evolution that helps explain the phenomena of anxiety, depression, and PTSD. In our state space models, we explore the functional relationship between perceived Chornobyl related health and PTSD, which provides a longitudinal explanation for hypothesis 6. In that sense, this paper complements the PTSD analysis in a separate paper. It does not deal with hypothesis 3, however.

We show how the phenomena addressed in those hypotheses exhibits duration dependence and autoregressive characteristics which partly explains direct effects of the psychological phenomena upon themselves. In this paper we will show the extent to which these prominent mental illnesses exhibit duration dependence, and reflect the impact of relevant events. We also examine possible cross-correlations among them to ascertain whether we should explore transfer functions among them.

2.0.3 Files containing the analysis

The paper is based on tests performed to answer these hypotheses. To facilitate organization on the part of the reader and to help find supporting evidence, the tests are located in files listed in Table 1.

In an exploratory mode, following the suggestions of Chris Sims, we use a vector autoregression analysis [15]. Although we do not employ Bayesian analy-

Table 1: Files on which this paper is based

File Type	Name	Version	Gender
dofile	varchorn.do	1	both
output	varanx.smcl, varanxdep.smcl,vardep.smcl	1	both
output	vardep.smcl, varptsd.smcl	1	both
output	femptsd.out	1	female
output	overallvar.smcl	1	both
output	mptsd.out	1	male
output	mUCMmodel1.out	2 and 3	male
output	fUCMptsd3.out	2 and 3	female
figure	mUCMmModel1.pdf	2 and 3	male
output	MaleUCMptsdmodel1.out	2 and 3	male
figure	mptsdResiduals1.pdf	2 and 3	male
figure	MUCMfilsig1.pdf	2 and 3	male
figure	fptsdPrdFil2.pdf	2 and 3	female
figure	femres1.pdf	2 and	female
figure	femres2.pdf	2 and 3	female
figure	fmucmPrdFilSig.pdf	2 and 3	female
figure	fptsdPrdFilSig2.pdf	2 and 3	female
report	AnxeityDepressionPTSDtsV3.tex	3	both
data	chwide16sep2012.dta, chornts2.dta, chornts.in7	2 and 3	both

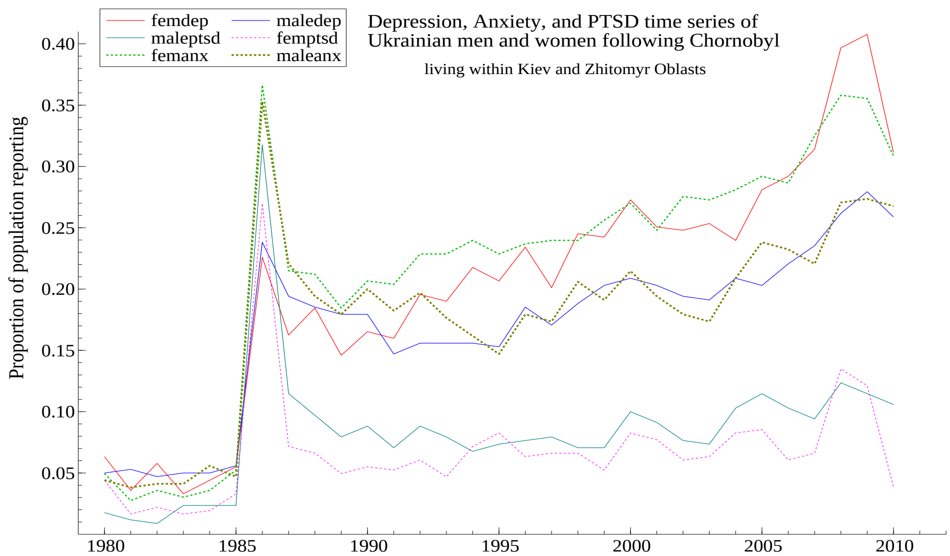

Figure 1: Time series of anxiety, depression, and PTSD among Ukrainian males and females

sis to implement noninformative prior variances, we do employ a Bayesian state space models (unobserved components models) to model the series afterward.

In Figure 1, we plot the time series of these mental illnesses, all of which seem to have been given a big boost by the incidence of the nuclear threat to which they were subjected in 1986. The pair of time series exhibiting the steepest slope at the highest level are the female anxiety and depression series (colored green and red). The pair of series just below the top pair are the male anxiety and depression series (blue and stone). The bottom series colored mint and pink happen to be the female and male PTSD series. As in previous analysis, the arrow of time proceeds from left to right.

The advantage of such a time series plot is that sudden spikes in the series or level shifts or slope shifts are indexed by time in the horizontal axis. This facilitates historical reconstruction and association of changes in longitudinal pattern with temporal anchor points. The pattern recognition that is supported by such a configuration can enhance an interpretation of past phenomena greatly.

In our modest time series analysis, we will endeavor to quantify the features of these series to allow us to use these series as a basis for explanation and prediction.

3 Time series regression models for Anxiety, Depression, and PTSD

3.0.4 Anxiety, Depression, and PTSD measures

These data come from self-reports of respondents estimating the level of symptoms on a scale of one to 100 over time. We collapsed the means of these variables over the years and obtained a summary score for each year, based on the recollection of the respondents. This was done separately for men and women to generate gender specific time series, which we examine here with a view toward identifying temporal patterns and possible orthogonalized impulse responses among the male and female versions of the same phenomena.

One of our objectives is to provide information that may be of help in the event of dealing with a nuclear incident. It is possible that self-reports may be one of the early forms of obtaining information about such an incident. Therefore, if we can ascertain the nature of these phenomenon and formulate it, we may be able to use that formulation for description, explanation, and prediction insofar as we can related it to other things impacting it.

An examination of the graph shows that the level of incidence of PTSD is lower than those of anxiety and depression. We begin by analyzing the simplest of these series first. So we will examine the PTSD series first. Prior to 1986, these series appear relatively stable and level. They are not far apart prior to Chornobyl. At the time of Chornobyl, however, things begin to happen. These series exhibit a sudden shock which drives them upward to the level of an outlier, and then more or less rapidly, to varying degrees, decline. Yet their decline is never to the previous level. They all exhibit a level shift upward after Chornobyl. The female PTSD series, represented by the pink dots, may exhibit a gradual increase in stochastic variance, whereas the male PTSD series, may appear to be slightly less volatile over time.

All of the series exhibit evidences of nonstationarity. The sudden change in mean level, the slight trend upward, and possibly increasing stochastic variance pose a challenge to conventional time series analysis.

3.0.5 Analysis of PTSD among Chornobyl survivors

The software developed by Sir David F. Hendry and Jurgen Doornik endeavors to deal with level shifts and outliers with the inclusion of intervention or event dummy variables to represent such changes. It provides tests of the assumptions in the output so we can know to what extent we can rely on the model for statistical validity. The model output for the male PTSD phenomenon is

$$MalePTSD_t = 0.020 + 0.244Chornblip + 0.0489Chornlevel + 0.142MalePTSD_{t-1} \quad (1)$$

where Chornblip is the outlier for the 1986 year coded 1 for that year and zero otherwise, Chornnlevel = level shift dummy variable coded 0 prior to 1985 and 1 for years thereafter, is listed on the next page. The purpose of the outlier

Table 2: Male PTSD time series regression model- following page

dummy is to capture the spike in the PTSD at the time of Chornobyl and the purpose of the level shift dummy is the capture the level shift in PTSD that follows Chornobyl. The output of the program is contained on the next page and with it the results of the misspecification tests, revealing that in most respects this model fulfills the assumptions required for statistical validation.

Although the goodness of fit indicated by the Adjusted R^2 is high, this is often the case where the residuals are serially correlated.Hence, we do not stress this aspect of the model. Because ewe used Newey-West robust standard-errors, we control for such inflation in the significance tests. Because they are based on White sandwich asymptotic variance estimates, they accommodate situations of heteroskedasticity as well.

There are problems with parameter stability. The forecast capability of the model is limited by failure of the Chow tests for parameter constancy. This means that there are some parameter constancy issues that require resolution for a perfect model. The problem is that there are end effects in the series that bring about sudden changes in the data shortly before or after the point of forecast horizon. For this reason, I will follow this model up with a model that can model nonstationary processes– namely, the state space unobserved components model. In the meantime, it is enough to show the event dependence with these models, which may be of interest in view of what could happen in similar nuclear incidents or accidents. This may be one of those circumstances in which we are reminded of George Box's proverb– that all models are wrong, but that some are useful.

Nevertheless, this model fulfills most of the tests for model validity– given in the block of test results below the Chow test. From there, we see that there is no serial correlation problem at lags 1 or 2, no immediate ARCH effects, the residuals are normally distributed and the heteroskedasticity tests due to White are fulfilled as well. The Ramsey reset test for functional specification is also satisfied. In general, the model is not a bad model for male PTSD. What this model is is to quantify the dependence of the series on the shock of the Chornobyl in 1986 and the level shift generated by it.

We also present the female model for Chornobyl PTSD. This model is very much like the male model except that it contains a deterministic trend to account for the enhanced slope in this model. In order to quantify the relationships on the events under consideration, we present the formula for the female PTSD model after the male output.

$$\begin{aligned} FemalePTSD_t = 0.0159 + 0.218Chornblip + 0.025Chornlevel \\ +0.078femalePTSD_{t-1} + 0.0011Trend \end{aligned} \tag{2}$$

The trend variable is simply a deterministic linear trend characterized by a unit change in level per each time period by which the analysis is performed.

```
 EQ(28) Modelling maleptsd by OLS
      The dataset is: Chornts.in7
      The estimation sample is: 1983 - 2004

                 Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
maleptsd_1          0.141999    0.04375    0.01465     9.69  0.0000   0.8392
Constant           0.0208843   0.005986  0.0005410     38.6  0.0000   0.9881
chornlevel         0.0489220   0.007230   0.003271     15.0  0.0000   0.9255
chornblip           0.244500    0.01101   0.003171     77.1  0.0000   0.9970

sigma              0.0102716  RSS              0.0018991208
R^2                 0.972278  F(3,18) =     210.4 [0.000]**
Adj.R^2             0.967658  log-likelihood        71.7148
no. of observations       22  no. of parameters           4
mean(maleptsd)     0.0858289  se(maleptsd)        0.0571155
When the log-likelihood constant is NOT included:
AIC                 -8.99377  SC                   -8.79540
HQ                  -8.94704  FPE               0.000124690
When the log-likelihood constant is included:
AIC                 -6.15589  SC                   -5.95752
HQ                  -6.10916  FPE                0.00212963

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast  Chi^2(6)   =    38.515 [0.0000]**
Chow      F(6,18)    =    5.0040 [0.0035]**

AR 1-2 test:       F(2,16)    =  0.70065 [0.5109]
ARCH 1-1 test:     F(1,20)    =0.00021317 [0.9885]
Normality test:    Chi^2(2)   =   3.9902 [0.1360]
Hetero test:       F(3,17)    =   1.0331 [0.4029]
Hetero-X test:     F(3,17)    =   1.0331 [0.4029]
RESET23 test:      F(2,16)    = 0.019113 [0.9811]

maleptsd =  + 0.142*maleptsd_1 + 0.0209 + 0.0489*chornlevel + 0.244*chornblip
(SE)         (0.0438)           (0.00599)  (0.00723)          (0.011)
```

Figure 2: Male PTSD time series AutoMetrics output

Although the trend is a small one, it is statistically significant so we leave it in the model. Both models have lagged endogenous variables and fit the data very well. However, there are structural breaks in the data that render the data less than easy to model as well as forecast. Like the male model, this model in all aspects but parameter constancy fits the data well and satisfies the tests of the other assumptions. The partial R^2 provided in the model output can be used as forms of β weights. The quantitative dependency on the autoregressive as well as the impact of the events are well formulated in this model and it helps to be able to understand these relationships before we examine the interrelationships among these series.

What is particularly interesting is the fact that the male and the female analysis of depression and anxiety seem to pair off with one another in Figure 1. The depression patterns are represented by the dark red and dark blue series, whereas the anxiety patterns are represented by the light green and stone series. Nonetheless, we will examine the depression series next and so we can eventually compare their parameter estimates with one another, we will use the same type of models for depression and anxiety.

3.0.6 Analysis of Anxiety among Chornobyl survivors

When people are confronted with a crisis–one of those situations with sudden threat of extreme or massive danger, with little time to respond, normal people naturally experience a rise in anxiety level. Situations of high anxiety under such crisis conditions are natural. The questions arise about how high this level rises and at what point it impairs rational and efficient behavior and at what level does it spawn panic are subjects of interest. Such psychological matters are of public interest in preparation for or modulation of such a public mood.

Hence, we will focus on the anxiety blip, level shift, and slope changes experienced by those who have survived Chornobyl in this analysis. First we examine a model for male anxiety in Figure 4.

$$\begin{aligned} MaleAnxiety_t = 0.038 + 0.305 Chornblip + 0.107 Chornlevel_{t-1} \\ +0.216 maleAnxiety_{t-1} \end{aligned} \tag{3}$$

This male anxiety model, like those considered before it, fits the data very well, as we can tell from the adjusted $R^2 = .956$. But we need not make too much of this. It is more important that most of the misspecification tests are passed, with the exception, as those that we examined before, which failed the stability and parameter constancy tests. However, the failure of the stability tests to compute and the failure of the parameter constancy tests appear to plague many nonstationary models. After discussing the depression models, we will explain how time varying parameter models–such as the state space models–can manage such circumstances. Nonetheless, the problems that the failure of such tests can be illustrated with respect to their implications for forecasting as we do in Figure 5.

In the meanwhile, it is useful to appreciate that the general regression assumptions are satisfied by these models as can be observed in the block of test results under the Chow test results in the output.

In Figure 6, we find the output of the female anxiety model. In this model, the formula generated is

$$\begin{aligned} FemaleAnxiety_t = 0.011 + 0.193 Chornblip + 0.122 Chornlevel_{t-1} \\ + 0.111 femaleAnxiety_{t-1} + 0.005 Trend \end{aligned} \tag{4}$$

The same pattern emerges in the female anxiety model is did with the male model, except that a slight trend is significant in addition to the other parameters. The same problem persists with parameter constancy and model stability due to the Chow tests. What this means is that the model may fit the data well, but for longer term forecasting it is of dubious utility. That notwithstanding, if the individual does not have highly sophisticated software, this approach may due in the short-term.

Table 3: Female PTSD time series regression model

```
EQ(30) Modelling femptsd by OLS
       The dataset is: Chornts.in7
       The estimation sample is: 1983 - 2004

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
femptsd_1           0.0782438    0.05283    0.01822     4.29  0.0005   0.5203
Constant            0.0159175   0.006588   0.003761     4.23  0.0006   0.5131
chornlevel          0.0249725   0.009606   0.006376     3.92  0.0011   0.4744
chornblip            0.218753    0.01198   0.004571     47.9  0.0000   0.9926
Trend              0.00110611  0.0004906  0.0003376     3.28  0.0045   0.3870

sigma               0.0102003  RSS              0.0017687676
R^2                  0.964186  F(4,17) =      114.4 [0.000]**
Adj.R^2               0.95576  log-likelihood         72.497
no. of observations        22  no. of parameters           5
mean(femptsd)       0.0686201  se(femptsd)         0.0484955
When the log-likelihood constant is NOT included:
AIC                  -8.97397  SC                   -8.72601
HQ                   -8.91556  FPE               0.000127692
When the log-likelihood constant is included:
AIC                  -6.13609  SC                   -5.88813
HQ                   -6.07768  FPE                0.00218091

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast   Chi^2(6)   =    68.947 [0.0000]**
Chow       F(6,17)    =    11.348 [0.0000]**

AR 1-2 test:       F(2,15)    =   1.8949 [0.1846]
ARCH 1-1 test:     F(1,20)    = 0.062575 [0.8050]
Normality test:    Chi^2(2)   =  0.20716 [0.9016]
Hetero test:       F(5,15)    =  0.50258 [0.7698]
Hetero-X test:     F(6,14)    =  0.81635 [0.5749]
RESET23 test:      F(2,15)    =  0.59171 [0.5658]

femptsd =  + 0.0782*femptsd_1 + 0.0159 + 0.025*chornlevel + 0.219*chornblip
(SE)        (0.0528)           (0.00659)  (0.00961)          (0.012)
           + 0.00111*Trend
            (0.000491)
```

Figure 3: Female PTSD time series model

```
EQ(46) Modelling maleanx by OLS
       The dataset is Chornts.in7
       The estimation sample is: 1983 - 2004

                  Coefficient  Std.Error     HACSE  t-HACSE  t-prob Part.R^2
maleanx_1            0.216239    0.08986   0.05605     3.86  0.0012   0.4526
Constant            0.0380753    0.01014  0.003253     11.7  0.0000   0.8839
chornblip            0.304690    0.01852  0.001980     154.  0.0000   0.9992
chornlevel_1         0.107341    0.01676   0.01273     8.43  0.0000   0.7979

sigma               0.0160353  RSS            0.00462837641
R^2                  0.948013  F(3,18) =     109.4 [0.000]**
Adj.R^2              0.939349  log-likelihood       61.9159
no. of observations        22  no. of parameters          4
mean(maleanx)        0.176203  se(maleanx)        0.0651115
When the log-likelihood constant is NOT included:
AIC                  -8.10296  SC                  -7.90458
HQ                   -8.05622  FPE              0.000303883
When the log-likelihood constant is included:
AIC                  -5.26508  SC                  -5.06671
HQ                   -5.21835  FPE               0.00519017

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast  Chi^2(6)  =   73.790 [0.0000]**
Chow      F(6,18)   =   7.6317 [0.0003]**

AR 1-2 test:      F(2,16)   =  0.51274 [0.6084]
ARCH 1-1 test:    F(1,20)   = 0.023189 [0.8805]
Normality test:   Chi^2(2)  =   1.3330 [0.5135]
Hetero test:      F(3,17)   =   1.8996 [0.1680]
Hetero-X test:    F(3,17)   =   1.8996 [0.1680]
RESET23 test:     F(2,16)   = 0.053250 [0.9483]

maleanx =  + 0.216*maleanx_1 + 0.0381 + 0.305*chornblip + 0.107*chornlevel_1
(SE)        (0.0899)          (0.0101)  (0.0185)          (0.0168)
```

Figure 4: Male anxiety model

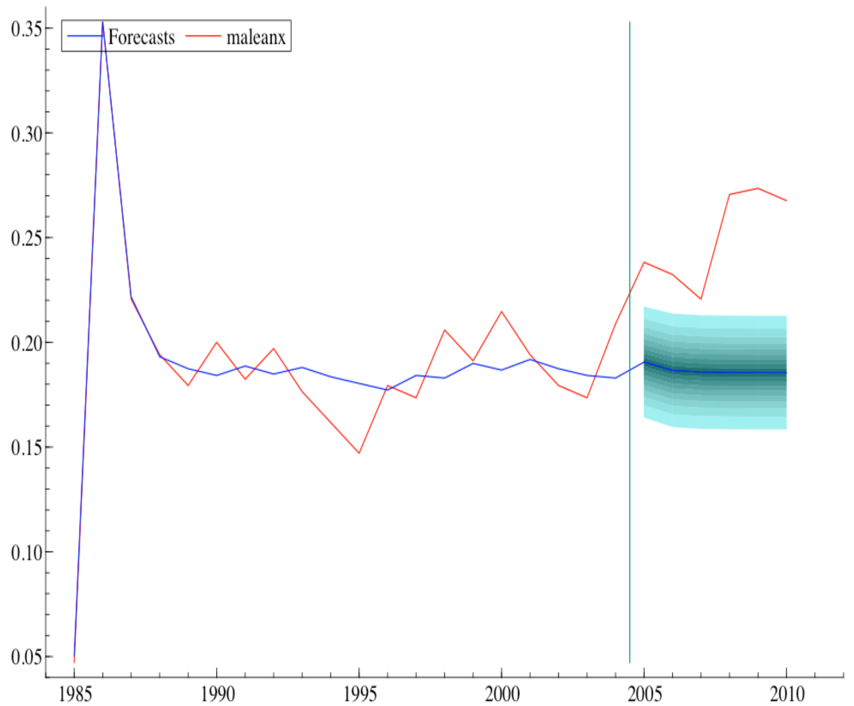

Figure 5: Example of end-effect in male anxiety data within forecast horizon

3.0.7 Analysis of Depression among Chornobyl survivors

A similar situation arises with the depression models. The female model has a slight significant trend, whereas the male model is more stable. However, they both have problems with extended model stability and parameter constancy, although in the short run they fit the data well and satisfy most of the other regression assumptions necessary for ordinary least squares estimation. What they all show is that there is a shock to the public mood and collective consciousness that strikes anxiety in most and depression in many. From such a model comes the autoregressive endogenous lagged variable model of

$$\begin{aligned} MaleDepress_t = 0.0233 + 0.131 chornblip + .051 chornlevel \\ +0.584 MaleDepress_{t-1} \end{aligned} \tag{5}$$

```
EQ(48) Modelling femanx by OLS
       The dataset is: Chornts.in7
       The estimation sample is: 1983 - 2004

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
femanx_1             0.110678    0.06093    0.03209     3.45  0.0031   0.4116
Constant            0.0131144   0.006261   0.003599     3.64  0.0020   0.4385
chornblip            0.193255    0.01522   0.008990     21.5  0.0000   0.9645
chornlevel           0.122574    0.01405    0.01063     11.5  0.0000   0.8866
Trend              0.00452219  0.0004521  0.0002984     15.2  0.0000   0.9311

sigma              0.00975782  RSS              0.00161865732
R^2                  0.988161  F(4,17) =      354.7 [0.000]**
Adj.R^2              0.985375  log-likelihood         73.4726
no. of observations        22  no. of parameters            5
mean(femanx)         0.216003  se(femanx)           0.0806872
When the log-likelihood constant is NOT included:
AIC                  -9.06266  SC                    -8.81469
HQ                   -9.00424  FPE                0.000116855
When the log-likelihood constant is included:
AIC                  -6.22478  SC                    -5.97681
HQ                   -6.16637  FPE                 0.00199582

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast  Chi^2(6)  =   64.167 [0.0000]**
Chow      F(6,17)   =   6.9070 [0.0008]**

AR 1-2 test:      F(2,15)   =   1.4768 [0.2597]
ARCH 1-1 test:    F(1,20)   = 0.099440 [0.7558]
Normality test:   Chi^2(2)  =   1.4568 [0.4827]
Hetero test:      F(5,15)   =  0.99457 [0.4537]
Hetero-X test:    F(6,14)   =  0.81201 [0.5778]
RESET23 test:     F(2,15)   =  0.45682 [0.6418]

femanx =  + 0.111*femanx_1 + 0.0131 + 0.193*chornblip + 0.123*chornlevel
(SE)       (0.0609)         (0.00626)  (0.0152)          (0.014)
          + 0.00452*Trend
           (0.000452)
```

Figure 6: Female anxiety model

$$FemaleDepress_t = 0.012 + 0.075chornblip + .0941chornlevel \\ +0.006Trend \quad (6)$$

It is possible that women feel more biologically vulnerable to such a health threat to their reproductive system and to their children who are especially vulnerable at an early age to the danger of thyroid cancer. The delay in notification instilled fear in some that they may have consumed contaminated substances before they were warned. This may have made many feel as though they had been unknowingly injured by exposure.

There are still some issues that we may explore more deeply with Vector Autoregression. By putting all of the series in the model, inverting the autoregressive system into a moving average system and then orthogonalizing the impacts and response, we may obtain a sense of whether there is a cross-fertilization of a unit impulse from one-series on the impact of another. We may be able to find a cointegrating vector that allows us to analyze nonstationary series together in such a form with a cointegrating vector autoregression.

```
EQ(50) Modelling maledep by OLS
       The dataset is:Chornts.in7
       The estimation sample is: 1983 - 2004

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
maledep_1            0.584520     0.1492     0.1770     3.30  0.0040   0.3773
Constant            0.0233078    0.01112   0.009023     2.58  0.0188   0.2704
chornblip            0.131305    0.02409    0.02229     5.89  0.0000   0.6585
chornlevel          0.0509580    0.02190    0.02323     2.19  0.0416   0.2109

sigma               0.0145062  RSS           0.00378773882
R^2                  0.931535  F(3,18) =      81.64 [0.000]**
Adj.R^2              0.920125  log-likelihood        64.1207
no. of observations        22  no. of parameters           4
mean(maledep)        0.166043  se(maledep)         0.0513271
When the log-likelihood constant is NOT included:
AIC                  -8.30339  SC                   -8.10502
HQ                   -8.25666  FPE               0.000248690
When the log-likelihood constant is included:
AIC                  -5.46552  SC                   -5.26714
HQ                   -5.41878  FPE                0.00424749

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast  Chi^2(6)   =    35.673 [0.0000]**
Chow      F(6,18)    =    2.6894 [0.0482]*

AR 1-2 test:       F(2,16)    =   1.5201 [0.2487]
ARCH 1-1 test:     F(1,20)    =  0.51807 [0.4800]
Normality test:    Chi^2(2)   =   1.3714 [0.5037]
Hetero test:       F(3,17)    =  0.51972 [0.6744]
Hetero-X test:     F(3,17)    =  0.51972 [0.6744]
RESET23 test:      F(2,16)    =  0.86953 [0.4380]

maledep =  + 0.585*maledep_1 + 0.0233 + 0.131*chornblip + 0.051*chornlevel
(SE)        (0.149)           (0.0111)  (0.0241)          (0.0219)
```

Figure 7: Male depression model

```
EQ(52) Modelling femdep by OLS
       The dataset is: Chornts.in7
       The estimation sample is: 1983 - 2004

                  Coefficient  Std.Error      HACSE  t-HACSE  t-prob Part.R^2
Constant            0.0119564    0.01037   0.005172     2.31  0.0328   0.2289
chornblip           0.0749565    0.01863   0.009153     8.19  0.0000   0.7884
chornlevel          0.0940134    0.01359    0.01094     8.59  0.0000   0.8040
Trend              0.00642414  0.0007582  0.0009459     6.79  0.0000   0.7193

sigma               0.0167233  RSS            0.00503405561
R^2                  0.949133  F(3,18) =       112 [0.000]**
Adj.R^2              0.940655  log-likelihood         60.9916
no. of observations        22  no. of parameters            4
mean(femdep)         0.189707  se(femdep)           0.0686487
When the log-likelihood constant is NOT included:
AIC                  -8.01894  SC                    -7.82056
HQ                   -7.97221  FPE                0.000330519
When the log-likelihood constant is included:
AIC                  -5.18106  SC                    -4.98269
HQ                   -5.13433  FPE                 0.00564509

Instability tests failed to compute.
This could be caused by the presence of dummy variables.

1-step (ex post) forecast analysis 2005 - 2010
Parameter constancy forecast tests:
Forecast  Chi^2(6)   =   85.264 [0.0000]**
Chow      F(6,18)    =   8.9412 [0.0001]**

AR 1-2 test:      F(2,16)    =  0.85690 [0.4431]
ARCH 1-1 test:    F(1,20)    =  0.28272 [0.6008]
Normality test:   Chi^2(2)   = 0.056865 [0.9720]
Hetero test:      F(3,17)    =  0.80101 [0.5103]
Hetero-X test:    F(3,17)    =  0.80101 [0.5103]
RESET23 test:     F(2,16)    =  0.93333 [0.4136]

femdep =  + 0.012 + 0.075*chornblip + 0.094*chornlevel + 0.00642*Trend
(SE)       (0.0104)  (0.0186)          (0.0136)           (0.000758)
```

Figure 8: Female depression model

4 Exploratory Vector Autoregression

In this case, before differencing the variables to render them covariance stationary, we explore their orthogonalized impulse responses and the roots of the companion matrix to ascertain whether the model is sufficiently stable to trust. Putting all of these measures together generates an unstable model. With all of the parameters in the model, there would not be enough power for the analysis under with a full model and we would find that one of the moduli resides almost on the unit circle indicated that a full model would teeter on the boundary of instability. However, if we treat the measures in pairs that appear to go together from Figure 1, we may be able to garner some information about the direction impulse and the shape of the impulse response functions, before proceeding to the state space analysis.

The first vector autoregression we examine will be that of male and female anxiety. We want to know how they affect one another. From Table 4 we observe the impact of one anxiety upon the other. The lagged impact tends to last no more than one year.

From this analysis, we can see that there is more of a tendency for previous (1 year prior) male anxiety and female anxiety to influence current female anxiety than both of these to influence current male anxiety. Because the modulus for the companion matrix of this equation equals 0.905, the model is stable.

Table 4: Exploratory Vector Autoregression

Table 3 varbasic maleanx femanx, lags(1/2)

Vector autoregression

Sample: 1982 - 2010		No. of obs	= 29
Log likelihood =	118.2769	AIC	= -7.467375
FPE =	1.97e-06	HQIC	= -7.319713
Det(Sigma_ml) =	9.83e-07	SBIC	= -6.995894

Equation	Parms	RMSE	R-sq	chi2	P>chi2
maleanx	5	.057532	0.4312	21.98016	0.0002
femanx	5	.059396	0.6367	50.82112	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
maleanx						
maleanx						
L1.	-.4074284	.5386332	-0.76	0.449	-1.46313	.6482733
L2.	.5503371	.5440754	1.01	0.312	-.5160312	1.616705
femanx						
L1.	.8110942	.506051	1.60	0.109	-.1807475	1.802936
L2.	-.4331821	.5116771	-0.85	0.397	-1.436051	.5696866
_cons	.0772964	.0278383	2.78	0.005	.0227343	.1318584
femanx						
maleanx						
L1.	-1.126684	.5560902	-2.03	0.043	-2.216601	-.0367672
L2.	.6098829	.5617088	1.09	0.278	-.4910461	1.710812
femanx						
L1.	1.487546	.522452	2.85	0.004	.4635589	2.511533
L2.	-.3798153	.5282604	-0.72	0.472	-1.415187	.6555561
_cons	.0791238	.0287405	2.75	0.006	.0227935	.1354542

4.0.8 Orthogonalized impulse response functions

Orthogonalized impulse response functions are ideal for analyzing conditions of comorbidity. They show the impact of one condition on the other as few things can.

This relationship may be observed in the orthogonalized impulse response functions by examining the off-diagonal patterns in the matrix graph of orthogonalized impulse response functions in Figure 9. In the upper right, we see that the female impact on the male tends to be a short increase in anxiety and then a reduction, whereas the influence of the male on the female anxiety (in the lower left) shows an exponential reduction in anxiety.

If we examine the impact of male and female depression on one another,

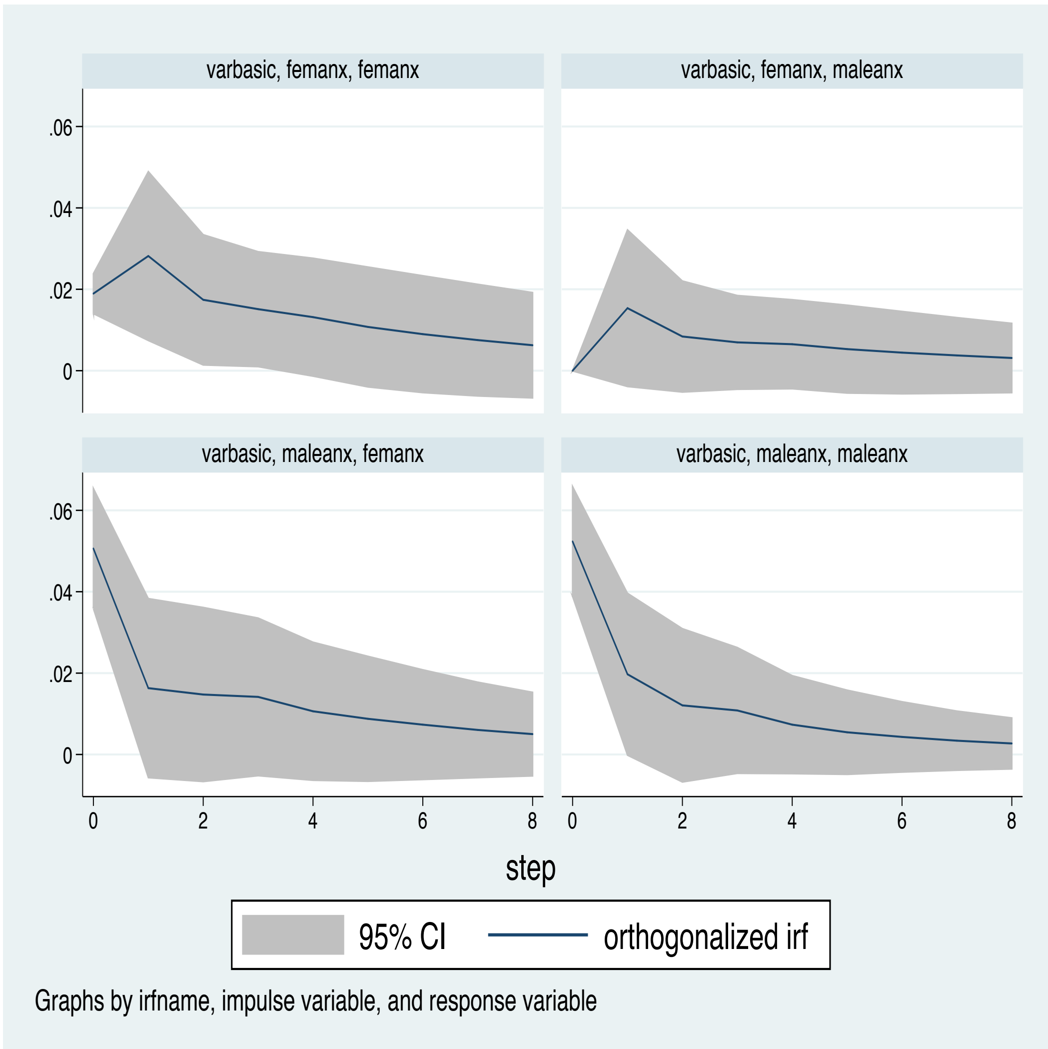

Figure 9: Influence of male and female anxiety on one another

Table 5: Vector Autoregression of male and female self-reported depression

we tend to obtain the results shown in Table 5, which reveals that in the case of depression on the part of both male and females, female depression at the current time tends to be driven by previous year's female depression and not the other way around.

```
Table 4   varbasic maledep femdep, lags(1/2)
Vector autoregression

Sample:  1982 - 2010                              No. of obs      =        29
Log likelihood =   126.168                        AIC             = -8.011587
FPE            =  1.14e-06                        HQIC            = -7.863925
Det(Sigma_ml)  =  5.70e-07                        SBIC            = -7.540105

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
maledep               5     .035898   0.7059   69.60845   0.0000
femdep                5     .045163   0.7937   111.5528   0.0000
----------------------------------------------------------------
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
maledep						
maledep						
L1.	.2929611	.3344395	0.88	0.381	-.3625284	.9484505
L2.	.09341	.3325114	0.28	0.779	-.5583004	.7451203
femdep						
L1.	.3150501	.2706373	1.16	0.244	-.2153892	.8454894
L2.	-.0192439	.2902661	-0.07	0.947	-.5881551	.5496672
_cons	.0516324	.01949	2.65	0.008	.0134326	.0898321
femdep						
maledep						
L1.	-.3080402	.4207506	-0.73	0.464	-1.132696	.5166158
L2.	.0274298	.4183249	0.07	0.948	-.7924719	.8473314
femdep						
L1.	.7850199	.3404824	2.31	0.021	.1176866	1.452353
L2.	.2737889	.365177	0.75	0.453	-.441945	.9895227
_cons	.0488096	.0245199	1.99	0.047	.0007514	.0968678

The modulus of this model 0.927, indicating that the model satisfies the stability requirements of the system.

The impulse response function from such a relationship may be illustrated in the upper left panel of Figure 10. This appears to be a more or less gradual diminution in the impact of the impulse over time.

If the reader is wondering how female anxiety acts on male depression or vice versa, we need to examine the next two vector autoregressions. The reader may wonder whether these impacts are reflexive or whether they are asymmetric.

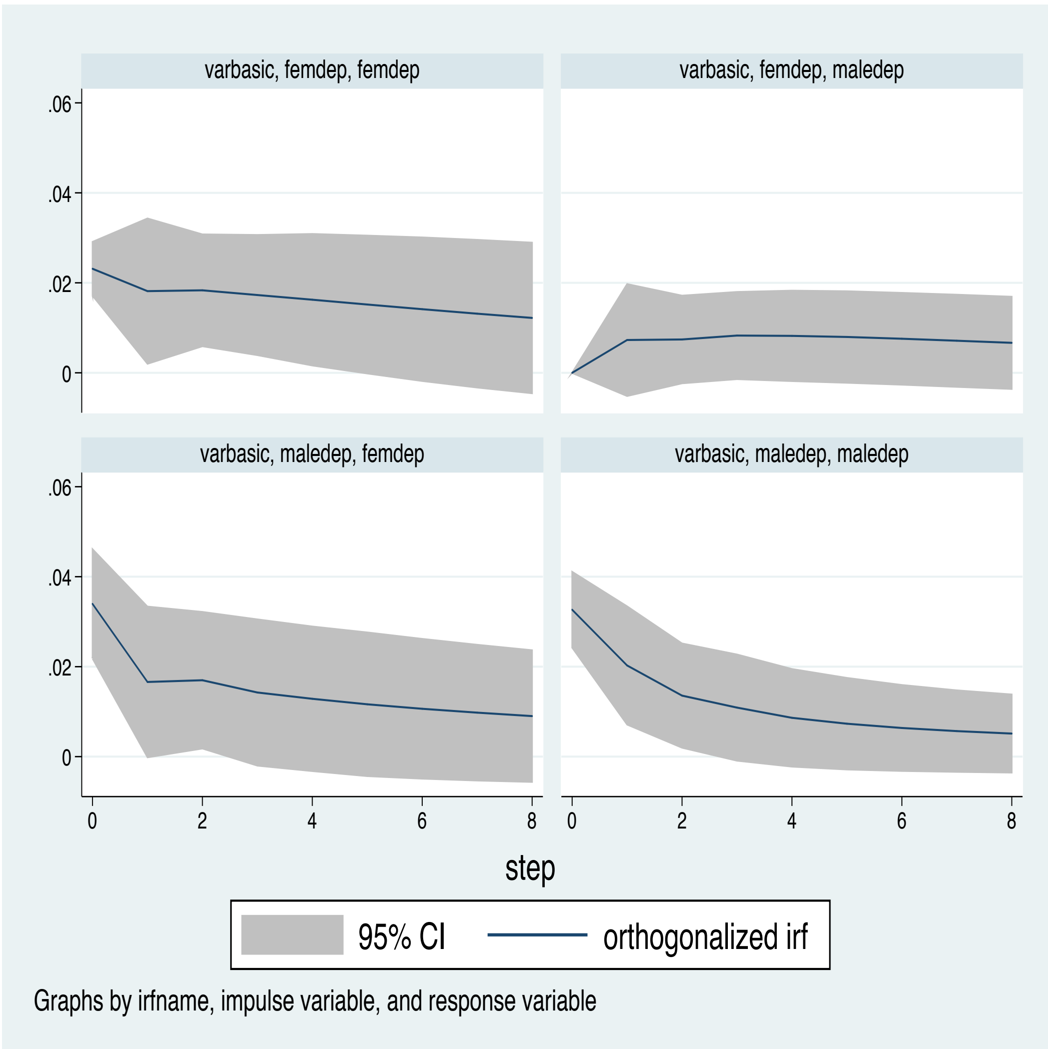

Figure 10: Influence of male and female depression on one another

Table 6: Vector Autoregression of female self-reported female anxiety and male depression

The data in Tables 4 and 5 will demonstrate that the answer to that question is that they are asymmetric and in what respects that is so. But before addressing that issue, we assure the reader that both of those analyses are based in stable equations. The modulus of the companion matrix of the first system is 0.8095, which satisfies the conditions of stability for the system, whereas the modulus for the companion matrix of the vector autoregression model in Table 5 is 0.905, which satisfies the condition of stability for that system as well.

```
Table 5  Vector autoregression of female anxiety and male depression

 varbasic femanx maledep, lags(1/2)
Vector autoregression
Sample:  1982 - 2010                                No. of obs      =        29
Log likelihood =   130.587                          AIC             = -8.316348
FPE            =  8.44e-07                          HQIC            = -8.168686
Det(Sigma_ml)  =  4.21e-07                          SBIC            = -7.844867
Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
femanx                5     .062848   0.5932   42.2947   0.0000
maledep               5     .036979   0.6879   63.92924  0.0000
----------------------------------------------------------------
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
femanx						
femanx						
L1.	.8877773	.5052778	1.76	0.079	-.1025491	1.878104
L2.	.1248608	.4883229	0.26	0.798	-.8322344	1.081956
maledep						
L1.	-.7212351	.894557	-0.81	0.420	-2.474535	1.032064
L2.	.3377894	.8186834	0.41	0.680	-1.2668	1.942379
_cons	.0763639	.0365764	2.09	0.037	.0046754	.1480524
maledep						
femanx						
L1.	.2422548	.2973003	0.81	0.415	-.340443	.8249526
L2.	.0545383	.2873241	0.19	0.849	-.5086067	.6176833
maledep						
L1.	.2736603	.5263481	0.52	0.603	-.7579631	1.305284
L2.	.1060058	.4817049	0.22	0.826	-.8381184	1.05013
_cons	.0486287	.0215212	2.26	0.024	.0064479	.0908095

From the above equation, it appears as though there may be a tendency (although not statistically significant at the 0.05 level) for female anxiety in the previous year to influence that in the current year. Otherwise, there is no clear

Table 7: Vector autoregression of male anxiety and female depression

asymmetry discernable.

However, when male anxiety and female depression are considered together, as shown in Table 7, there is a significant impact of previous year's female depression to impact current female depression. But male anxiety appears to have no significant impact on female depression. Nor does female depression appear to impact male anxiety much.

The vector autoregression model for male and female PTSD is not statistically significant so we do not elaborate on it. However, we will develop another kind of model that can explain PTSD for both men and women in the next section.

Vector autoregression of male anxiety and female depression

```
. varbasic femdep maleanx, lags(1/2)
Vector autoregression
Sample:  1982 - 2010                            No. of obs      =        29
Log likelihood =  109.3827                      AIC             = -6.853982
FPE            =  3.64e-06                      HQIC            =  -6.70632
Det(Sigma_ml)  =  1.82e-06                      SBIC            = -6.382501
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
femdep	5	.044925	0.7958	113.0477	0.0000
maleanx	5	.05862	0.4094	20.10511	0.0005

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
femdep						
femdep						
L1.	.9067017	.3812146	2.38	0.017	.1595348	1.653869
L2.	.0481945	.3953382	0.12	0.903	-.7266542	.8230432
maleanx						
L1.	-.2742497	.2741594	-1.00	0.317	-.8115922	.2630928
L2.	.1303219	.2591686	0.50	0.615	-.3776393	.6382831
_cons	.0461341	.0218269	2.11	0.035	.0033541	.0889141
maleanx						
femdep						
L1.	.3735188	.4974282	0.75	0.453	-.6014226	1.34846
L2.	-.1203546	.5158575	-0.23	0.816	-1.131417	.8907075
maleanx						
L1.	.1556096	.3577371	0.43	0.664	-.5455422	.8567614
L2.	.1617274	.3381764	0.48	0.632	-.5010862	.8245411
_cons	.0779438	.0284809	2.74	0.006	.0221222	.1337653

5 Co-volatility of anxiety

To what extent can a shock on the part of gender be communicated to the other gender. Which gender leads the other in terms of anxiety and which communicates it to which. How high is the dynamic conditional correlation of male anxiety with that of female anxiety. These are some of the questions we hope to address in understanding the spread of panic within this culture.

We are particularly interested in sharp increases in the dynamic conditional correlation in anxiety because they may indicates moments of crisis in which panic is developing and spreading and in which people may become hypervigilant.

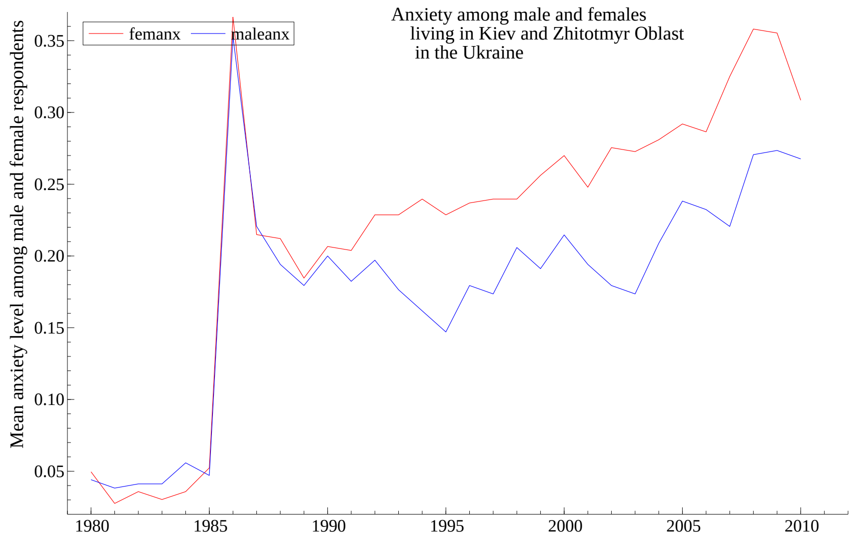

Figure 11: mean levels of anxiety among residents of Kiev and Zhitomyr Oblasts

5.1 Dynamic conditional correlation measures contagion of public anxiety

There are a variety of dynamic conditional correlation formulae. We chose the first in the sample that converged without a violation of an assumption, which happened to be the Tse and Tsui (2002) version, the formula for which is

$$R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \Psi_{t-1} + \theta_2 R_{t-1} \tag{7}$$

where θ_1 *and* θ_2 are non-negative parameters whose sum should be less than 1.

Table 8: Dynamic Conditional Correlation of Tse and Tsui (2002)

Laurent has written that for these conditional correlation models H_t can be written as

$$\begin{aligned} H_t &= D_t R_t D_t \\ D_t &= diag(h_{11t}^{1/2} ... h_{NNt}^{1/2}) \\ R_t &= \rho_{ijt} \ with \ \rho_{iit} = 1 \end{aligned} \tag{8}$$

so R_t = N x N *matrix of conditional correlations and* h_{iit} = conditional error variance such that $h_{ijt} = \rho_{ijt} sqrt(h_{iit} h_{jjt}) \ \ \forall_i \neq j$.

We used the G@RCH program of Professor Sebastien Laurent to arrive at these results. It offers a very wide and robust selection of multivariate GARCH programs with which to analyze co-volatility [14, 257-259].

```
Table 8: Dynamic conditional correlation between male and female anxiety
  *************
 ** SERIES  **
*************
#1: maleanx
#2: femanx

 *******************************
 ** MG@RCH(12) SPECIFICATIONS **
 *******************************
Conditional Variance : Dynamic Correlation Model (Tse and Tsui) with M = 2.
Multivariate Normal distribution.

Strong convergence using numerical derivatives
Log-likelihood = 133.588
Please wait : Computing the Std Errors ...

 Robust Standard Errors (Sandwich formula)
                  Coefficient  Std.Error  t-value  t-prob
alpha                0.000000 7.2201e-09   0.2659  0.7922
beta                 0.683086    0.44969    1.519  0.1396

Correlation-Targeting
rho_21               0.615432
No. Observations :        31  No. Parameters  :        15
No. Series       :         2  Log Likelihood  :   133.588
Elapsed Time : 0 seconds (or 0 minutes).
```

According to this output, the dynamic conditional correlation between the Ukrainian male and female anxiety within these two Oblasts is 0.615. This might be the level when the general level is gradually rising as is shown in Figure 11. In addition, it generates a graph of the dynamic correlation between male and female anxiety in Figure 12 so we can ascertain when it converges during a crisis. From this graph we can see a peak in 1986 and another as 2008 approaches, which is the time the global financial crisis emerged.

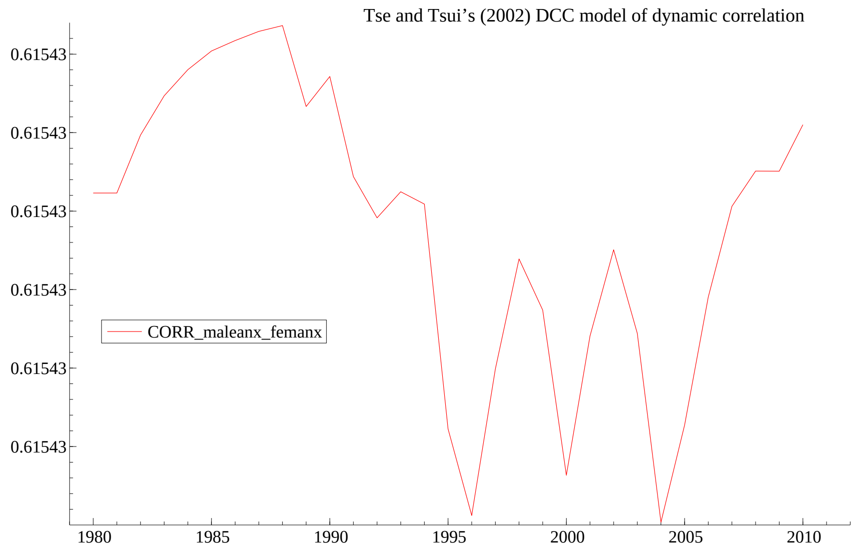

Figure 12: Dynamic Correlation between male and female anxiety revealing times of panic and crisis

The rise in general anxiety may signal the rise and/or spread of hypervigilance throughout the society, but it serves as an indicator by which many other analyses may be conducted to determine the relative amount of public unease and worry. It may serve as a public barometer for many other analysis.

6 State space models

6.1 Unobserved components in Chornobyl PTSD

A model that is particularly useful for incorporating time varying processes into the model either as level shift interventions or as time-varying exogenous variables is the state space model. We found that we have such processes at work in the estimation of PTSD. In Figure 13, we incorporate estimates of actual and perceived risk into the model for Chornobyl PTSD.

This filter and smoother, originally developed by Rudolf Kalman, in 1960, and Kalman and Bucy, 1961, allows accurate updating and prediction by one-step ahead autoregressive projection. The filtering process proceeds in phases and the filtering phase involves a Markovian process of one-step ahead forecasts of a state vector (comprised of time series structural components (mean-level, slope, seasonal, etc.)) and then a factor analytic model adjustment phase where a factor analysis adjusts the measurement model estimates for these components. This algorithm is reiterated until there is complete convergence of the

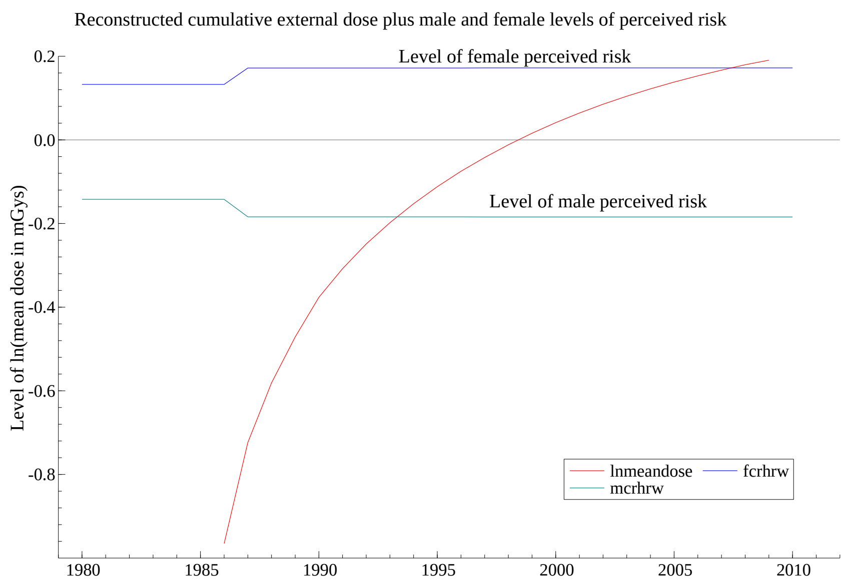

Figure 13: Levels of Ln(external dose in mGys) and perceived Chornobyl related health risk on the part of males and females

transition model that moves the process from one state to another over time and incrementally adjusts the measurement fittings as it proceeds. As the model estimates, it approaches a steady state and then finally converges as the likelihood is maximized and the prediction error variance is minimized. To capture the essence of the process in a nutshell, the Kalman filter uses a one-step ahead autoregressive projection and a regression on the innovation. It update the mean and the variance from an original state and converges to a steady state until a solution is found. Smoothing is accomplished by backwards recursions and entails the use of all to extract the signal from the noise.

6.1.1 The Kalman filter

The model has two fundamental equations. One is a state or transition equation of a state vector, α_t, consisting of a level, slope, seasonal, cyclical, intervention or event dummies and exogenous variables, entered as components. The transition equation is sometimes called the process equation. This autoregressive process is the way the state vector is moved ahead in time from one period to another. Durbin and Koopman [9, 65-81] explain the process, assuming that variables have been mean-centered:

$$\alpha_{t+1} = T_t \alpha_{t-1} + R_t \eta_t \quad with \quad \eta_t \sim NID(0, Q_t) \tag{9}$$

where the state vector, α_t is of order m x 1, consists of the structures inherent in the time series, T_t is an mxm transition matrix, R_t is a selection matrix of ones and zeros, and η_t is an $rx1$ vector of forecast errors. Yet there is an observation or measurement equation for the state vector:

$$y_t = Z_t\alpha_t + \epsilon_t \quad with \quad \epsilon \sim NID(0, H_t) \tag{10}$$

Forecast errors are computed as $\nu_t = \mathrm{y}_t - E(Z_t\alpha_t + \epsilon_t|Y_{t-1}) = y_t - Z_t\alpha_t$. The variance of the forecast error is based on the factor analytic equation:

$$F_t = Z_t P_t Z_t' + H_t \tag{11}$$

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 for the model with

$$\alpha_0 = (a_0, P_0) \tag{12}$$

such that α_0 comprises the initial state of the state vector.

The updating (filtering) is performed by taking the expectations

$$\alpha_{t+1} = T_t E(\alpha_t|Y_t), \tag{13}$$

$$and \tag{14}$$

$$P_{t+1} = Var(T_t\alpha_t + R_t\eta_t|Y_t) \tag{15}$$

which essentially results in a one-step ahead autoregressive forecast with a regression on the innovation where K_t is called the Kalman gain:

$$\alpha_{t+1} = T_t\alpha_t + K_t\nu_t \tag{16}$$

This allows the whole process to undergo Bayesian sequential updating, making it a particularly accurate observation-driven process.

6.1.2 Unobserved components

Other components the state vector may include are the mean level (μ_t), the slope, (β_t), and/or the seasonal component, which can consists of a set of dummy variables used to define annual variation, among others to form a basic structural model. A seasonal component, designating within period variations, as there are many seasonal variations over time, can be represented by dummy variables which sum to 0:

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + k_t \tag{17}$$

Commandeur and Koopman describe this process in [3, 32-34]. They also note that the state vector can include other kinds of components as well. It can include cyclical components which represent between period variations, can be represented by

$$\psi_{1t} = \psi_{t-1}\rho cos\phi + \psi_{t-1}\rho sin\phi + e_t \tag{18}$$
$$\psi_{2t} = \psi_{t-1}\rho cos\phi - \psi_{t-1}\rho sin\phi + e_t \tag{19}$$

The transition process represents a one-step ahead autoregressive plus a regression on the residuals. The updating takes place through a filtering process, which can be described, for the simplest local level model, by

$$\alpha_{t+1} = \alpha_t + K_t(y_t - \alpha_t) \tag{20}$$

where the state vector, α_t is a one-step ahead autoregressive projection plus a regression on the innovation with K_t = the Kalman gain.

Variance updating is accomplished through equations based on multivariate regression

The factor analytic adjustment of the measurement equation is analogous to a principal components analysis of a selection of components loaded into a state vector. Let α_t be a state vector. If C_t and D_t are vectors of constants, T_t is 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 have the basis of the transition equation.

If y_t is 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, as

$$\alpha_{t+1} = C_t + T_t\alpha_t + R\eta_t \qquad \eta \sim NID(0, H_t) \tag{21}$$
$$y_t \;=\; D_t + Z\alpha_t \;+\; \epsilon_t \qquad \epsilon \sim NID(0, Q_t) \tag{22}$$

We can use $_t$ to represent events or interventions and ω_t to represent exogenous variables.

Of course, α_t the state vector, can consisting of:

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

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.

Beginning with a diffuse prior, we obtain starting values for the mean and the variance. Because an infinite variance is not easy to come by a very large number is used instead (such as 10^6). Eventually, the system will converge to the correct estimate when this is implemented. It merely takes a little longer, but with the fast computers we have today, this is not a problem.

6.1.3 Augmentation of the Kalman filter

The augmented version as developed by DeJong [8], Harvey [10], Durbin and Koopman [9] basically partitions the state vector into stationary and nonstationary partitions and fits the partitioned segment by conventional means whereas the nonstationary partition uses a diffuse prior as a basis for beginning the maximum likelihood estimation, which generally iteratively converges upon the correct parameter and model solutions.

6.1.4 Advantages of the state space over earlier time series models

Unlike the Box-Jenkins Time Series models, the state space model with the augmented Kalman filter can handle nonstationary processes. It can handle missing data in a time series, which earlier models could not do. New innovations in the Koopman, Harvey, Doornik, and Shephard version of Stamp 8.3 identifies outliers and level shifts and allows automatic fitting of outliers and level shifts that can handle pre-forecast origin end-effects, as it nicely did in the female model that follows. The end-effects were described by Perez-Foster as a time when the global economic crisis was under way and when political transformation was taking place. These advantages make for a more robust time series model.

6.1.5 Male PTSD model

Using this technique to model the PTSD, we achieve steady state full convergence with the following model

$$\begin{aligned} MalePTSD_t = 0.731level_t + 0.889malePTSD_{t-1} \\ +0.294Chornobyl + 5.039PerceivedRisk_t \\ +0.019Int2008 \end{aligned} \tag{23}$$

where Int2008 is an outlier event dummy for the year 2008, Chornobyl is an event dummy for the year 1986, and level is a level shift dummy for 1986.

This model is robust to nonstationarity. It is a simple model as well and a better basis for predictions than earlier models. Using this model, we can see that the shock of the crisis as well as the lagged values of the shock and the level of male PTSD are the primary determinants of current male PTSD. In future research, we can test other exogenous variables to ascertain whether any of them help predict male self-reported Chornobyl PTSD.

The output for this model is given in Table 6 and the comparison of the data to the signal of the components can be found in Figure 14. In that output, mcrhrw = male Chornoobyl related health risk over multiple waves. Although the 2008 event is not quite statistically significant, we leave it in the model because it help explains the end-effect of 2008, which might be the onset of the global financial crisis and/or its accompanying political commotion which distracted people from PTSD.

As can be seen from the graphs as well as the output, the model fits the data very well and owing to its observation driven nature is quite robust to regimes shifts and other changes. A review of the residuals in Figure 15 shows how well-behaved the residuals are.

Moreoover, the model provides a reasonably good basis for filtering and smoothing, as shown by the filtered and smoothed values plotted against the data in Figure 16.

Table 9: Male state-space PTSD Model

```
Table 6  Male PTSD model

UC( 2) Estimation done by Maximum Likelihood (exact score)
The database used is chornts2.in7
The selection sample is: 1980 - 2010 (T = 31, N = 1)
The dependent variable Y is: maleptsd
The model is:  Y = Level + Irregular + AR(1) + Explanatory vars + Interventions
Steady state. found

Log-Likelihood is 120.993 (-2 LogL = -241.985).
Prediction error variance is 0.000135653

Summary statistics
                 maleptsd
 T                 31.000
 p                 3.0000
 std.error       0.011647
 Normality         2.1001
 H(9)              1.3313
 DW                1.7819
 r(1)             0.10238
 q                 7.0000
 r(q)            -0.16890
 Q(q,q-p)          15.580
 R^2              0.95849

 Variances of disturbances:
                    Value    (q-ratio)
Level         5.55340e-06  (  0.01740)
AR(1)         0.000319073  (    1.000)
Irregular     5.22763e-05  (   0.1638)

AR(1) other parameters:
AR coefficient     0.88910

State vector analysis at period 2010
             Value      Prob
Level      0.73134 [0.00000]

Regression effects in final state at time 2010

                    Coefficient        RMSE     t-value      Prob
Level break 1986(1)     0.29367     0.01248    23.53884 [0.00000]
Outlier 2008(1)         0.01904     0.01051     1.81191 [0.08114]
mcrhrw                  5.03902     0.29672    16.98239 [0.00000]
```

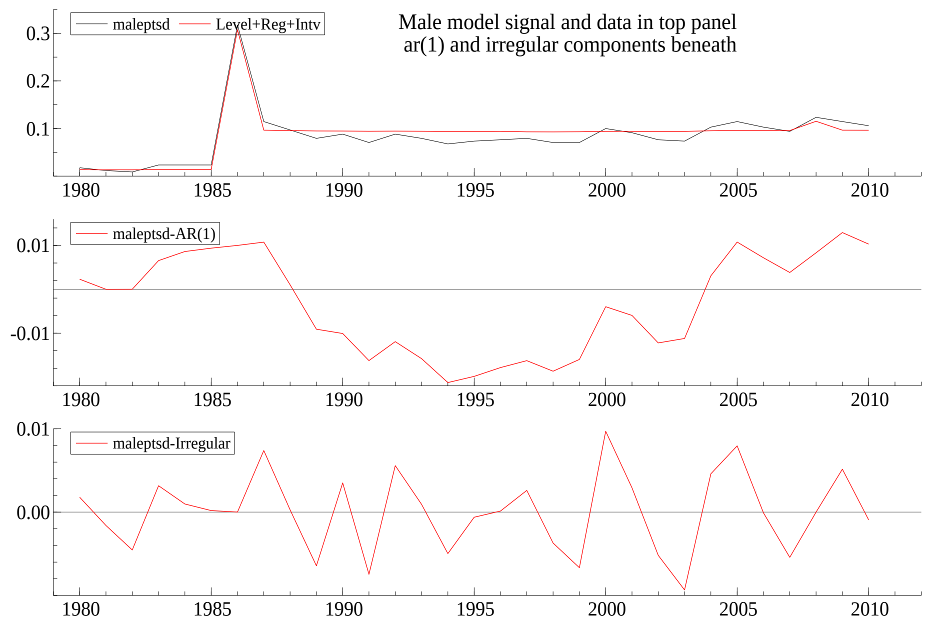

Figure 14: Unobserved components model of male Chornobyl PTSD

The male model residuals are reasonably well-behaved as can be seen from the diagnostic residual graphs below.

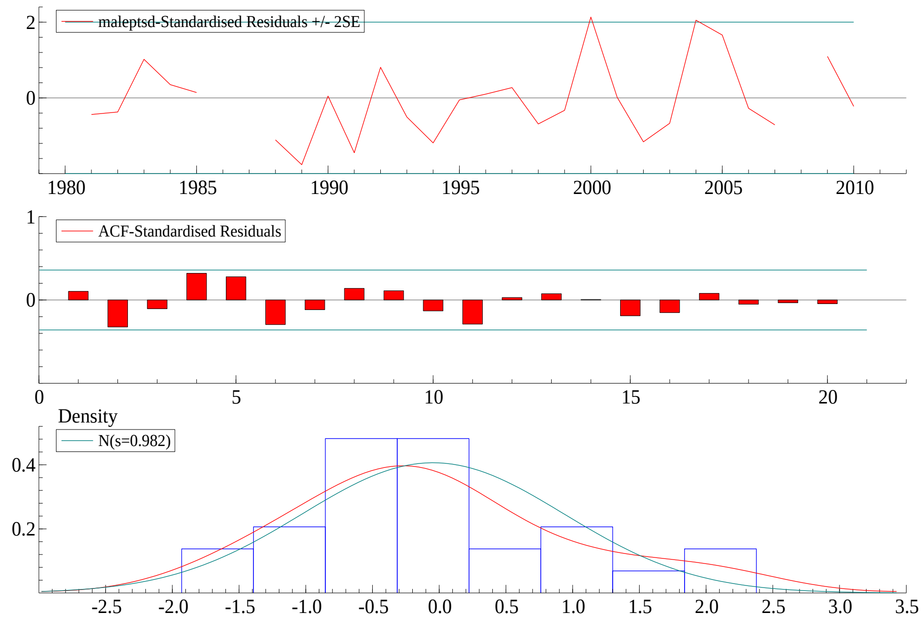

Figure 15: residuals of the male model

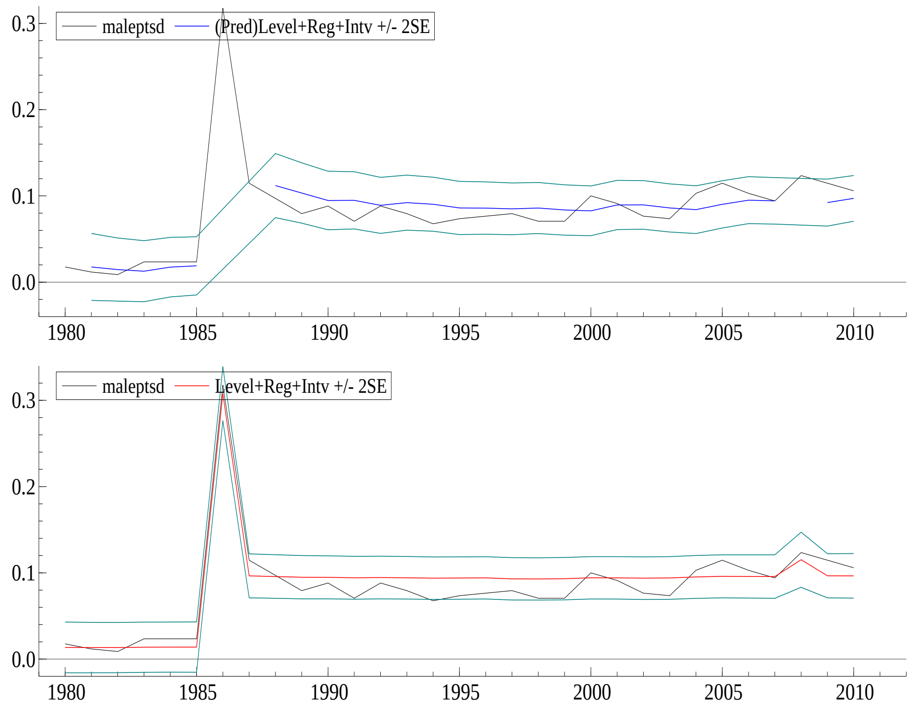

Figure 16: Predicted values and signal of male model on top and smoothed signal with confidence intervals on boottom

Table 10: Female state-space PTSD Model

6.1.6 Female PTSD model

The female PTSD model is also a function of the perceived Chornobyl related health risk, along with some other structural components. The structural components comprise a level shift at 1986, the time of Chornobyl, along with a outlier in 2008 at the time of the great economic recession and the accompanying political commotion.

```
Table 7  Female PTSD model

UC( 3) Estimation done by Maximum Likelihood (EM)
The database used is chornts2.in7
The selection sample is: 1980 - 2010 (T = 31, N = 1)
The dependent variable Y is: femptsd
The model is:  Y = Trend + Irregular + Explanatory vars + Interventions
Steady state. found

Log-Likelihood is 107.951 (-2 LogL = -215.902).
Prediction error variance is 0.000152871

Summary statistics
                  femptsd
 T                 31.000
 p                 2.0000
 std.error       0.012364
 Normality         1.1100
 H(8)              1.1810
 DW                2.0850
 r(1)           -0.076584
 q                 6.0000
 r(q)            -0.11192
 Q(q,q-p)          6.0808
 Rd^2             0.96600

 Variances of disturbances:
                    Value    (q-ratio)
Level         6.38769e-05  (   0.8723)
Slope         1.09906e-08  (0.0001501)
Irregular     7.32282e-05  (    1.000)


State vector analysis at period 2010
             Value      Prob
Level      0.68400 [0.00000]
Slope     -0.00108 [0.51225]

Regression effects in final state at time 2010

                    Coefficient        RMSE     t-value      Prob
Level break 1986(1)     0.24424     0.01371    17.81715 [0.00000]
Outlier 2008(1)         0.07813     0.01199     6.51867 [0.00000]
Outlier 2009(1)         0.07056     0.01227     5.75291 [0.00001]
fcrhrw                 -5.13594     0.35024   -14.66401 [0.00000]
```

The residuals of this female PTSD model are very well behaved also, as shown in Figure 17.

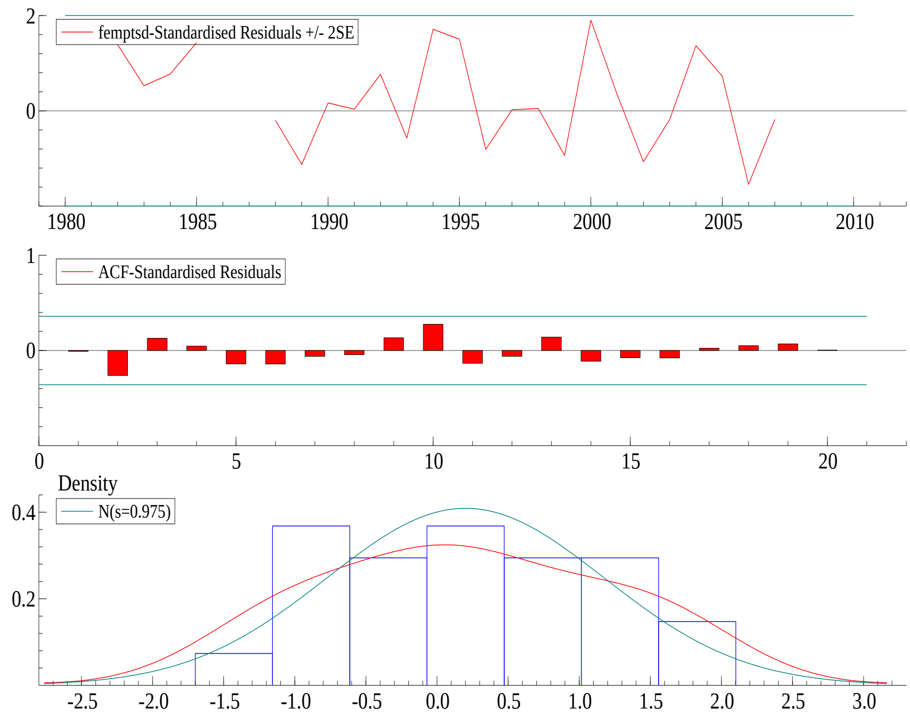

Figure 17: Female PTSD model residuals

How well this models the female self-reported Chornobyl PTSD is revealed in the following component and signal graph in Figure 18. In that figure the black line represents the data and the red line signifies the signal generated by the model. In both the male and female PTSD model the match is respectably acceptable. There is an end-effect in the data and this may reflect governmental turmoil at the time, but Stamp 8.3 is capable of identifying the outliers in automatic mode, constructing them, and inserting them, in order to improve accuracy generating the signal to match the data.

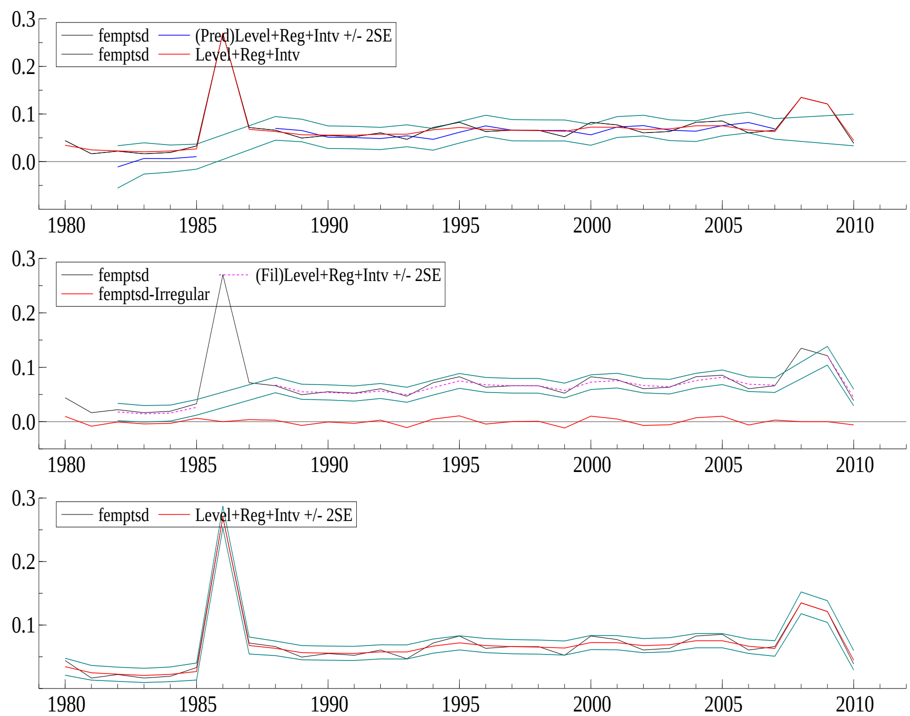

Figure 18: Predictions and signal against Female PTSD data

7 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. These findings may provide the basis for further studies in post-disaster research. We have explored comorbidity in exploratory vector autoregression, and have even shown how post-nuclear sequelae may be a function of perceived risk of exposure in the dspace models. These quantitative findings may provide the basis for further study of these phenomena, as well as for the study of treatment for such effects.

8 Directions for future research

We have just focused on structural time series. We have used the intervention of Chornobyl to quantify the impact it has had on levels of PTSD and in future research, we would like to test a variety of exogenous variables in rendering the fit more accurate and enhancing the capability to forecast the level of it.

We could also investigate other impulse response functions in various vector autoregressions on the BSI mental phenomena over time particularly with respect to their impact on other health behavior variables.

We have begun exploring the co-volatility of female and male anxiety as a form of co-morbidity with a multivariate GARCH model with a diagonal BEKK (Bollerslev, Engle, and Koner, 1995) configuration where

$$H_t = CC' + \sum_{k=1}^{K}\sum_{i=1}^{q} A_{ik}\epsilon_{t-i}\epsilon'_{t-1}A'_{ik} + \sum_{k=1}^{K}\sum_{i=1}^{q} B_{ik}H'_{t-1}B'_{ik} \tag{24}$$

Where $\epsilon_t = H_t^{1/2} z_t$, $E_{t-1}(\epsilon_{t)=0}$, and $H_t = is\ an\ NxN$ positive definite matrix generated as a σ field with past observations $\epsilon_{t-1}, \epsilon_{t-2}, ...$

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