

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

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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 Chernobyl nuclear incident among residents of the area. The survey respondents lived in either Kiev or Zhitomyr Oblasts. The Chernobyl nuclear plant was located near Pripjat 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 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.

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
report	AnxeityDepressionPTSDts.tex	1	both
data	chwide16sep2012.dta, chornts.dta, chornts.in7	1	both

In an exploratory mode, following the suggestions of Chris Sims, we use a vector autoregression analysis [12]. Although we do not employ Bayesian analysis 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.

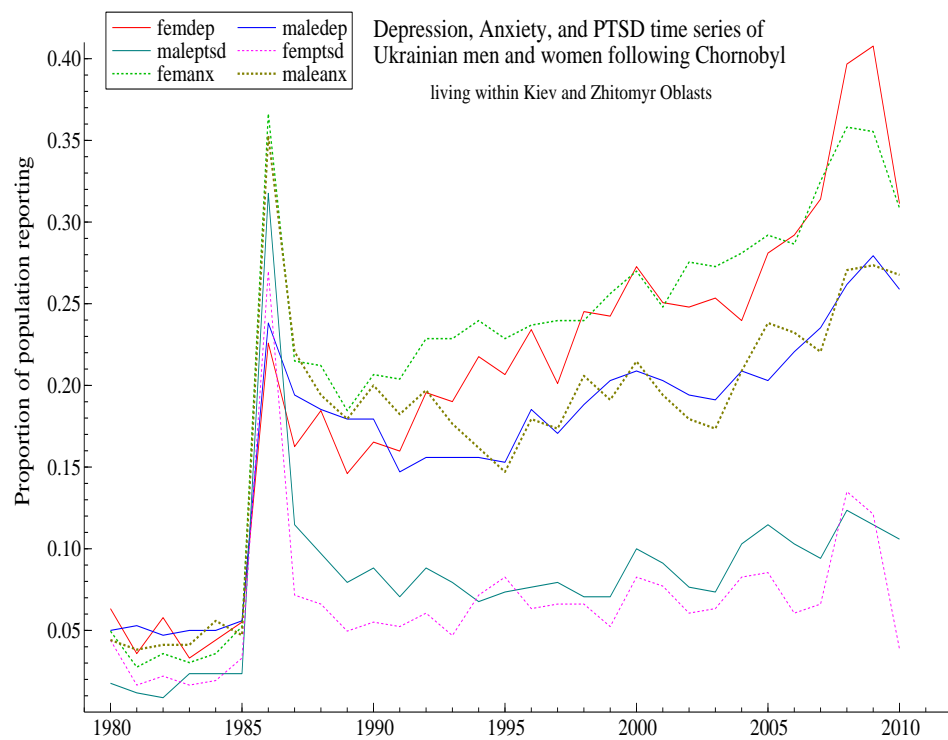


Figure 1: Time series of anxiety, depression, and PTSD among Ukrainian males and females

2.1 Time series for Anxiety, Depression, and PTSD

2.1.1 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.

2.1.2 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

$$MalePTSD_t = 0.209 + 0.244Chornblip + 0.0489Chornlevel + 0.143MalePTSD_{t-1} \quad (1)$$

where Chornblip is the outlier for the 1986 year coded 1 for that year and zero otherwise, Chornlevel = 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 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 Chernobyl. 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 we 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 Chernobyl in 1986 and the level shift generated by it.

We also present the female model for Chernobyl 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.

$$\begin{aligned} femalePTSD_t = & 0.0159 + 0.218Chornblip + 0.025Chornlevel \\ & + 0.078femalePTSD_{t-1} + 0.0011Trend \end{aligned} \quad (2)$$

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. 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

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

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.

2.1.3 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.

$$\begin{aligned} maleAnxiety_t = 0.038 + 0.305Chornblip + 0.107Chornlevel_{t-1} \\ + 0.216maleAnxiety_{t-1} \end{aligned} \quad (3)$$

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

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

The same pattern emerges in the female anxiety model as 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.

```

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

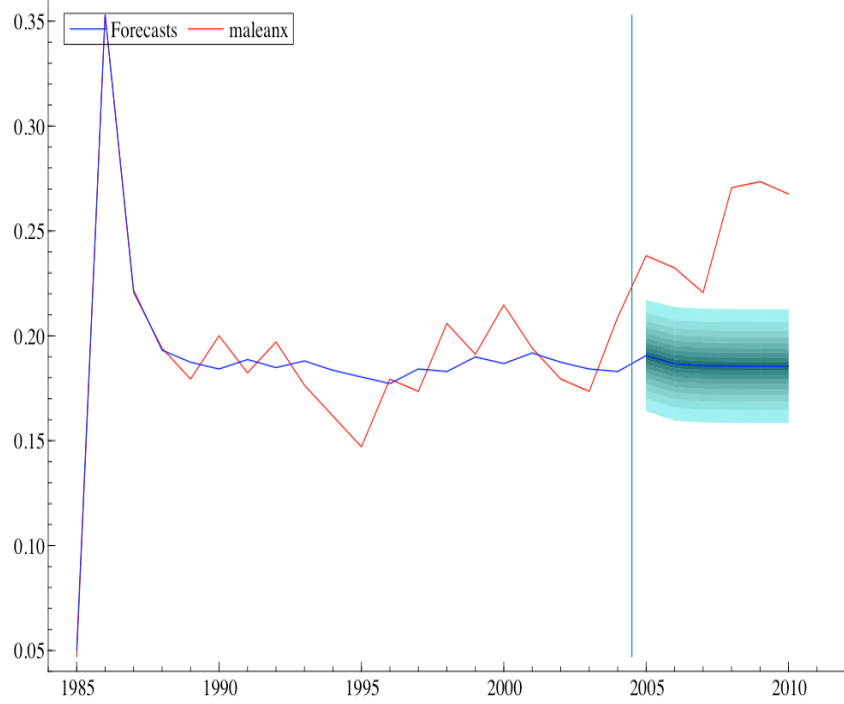


Figure 5: Example of end-effect in male anxiety data within forecast horizon

2.1.4 Analysis of Depression among Chernobyl 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

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

```

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

3 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 2 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 2 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

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, we tend to obtain the results shown in Table 3. Table 3 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.

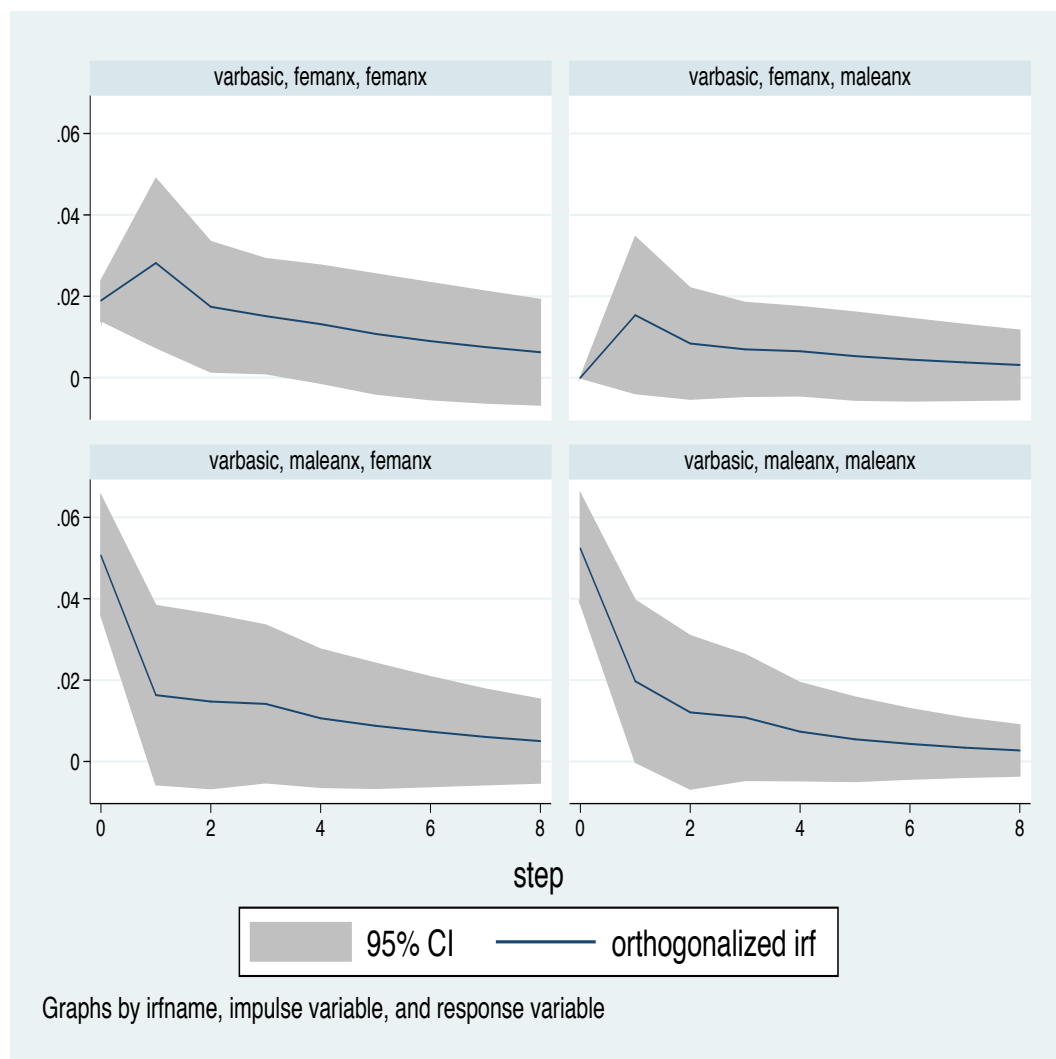


Figure 9: Influence of male and female anxiety on one another

Table 3 varbasic maledep femdep, lags(1/2)

Vector autoregression

Sample: 1982 - 2010
 Log likelihood = 126.168
 FPE = 1.14e-06
 Det(Sigma_ml) = 5.70e-07

No. of obs = 29
 AIC = -8.011587
 HQIC = -7.863925
 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. 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.

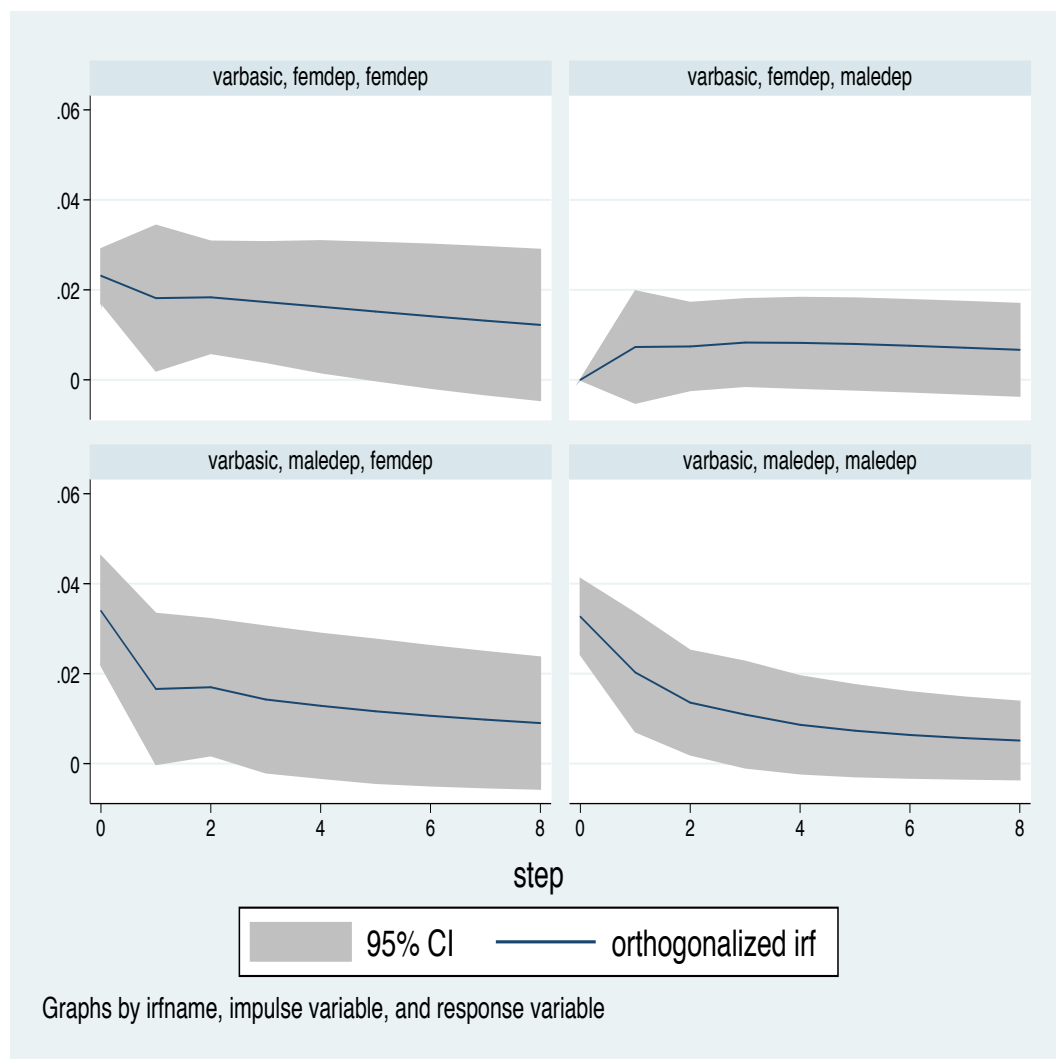


Figure 10: Influence of male and female depression on one another

Table 4 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 asymmetry discernable.

However, when male anxiety and female depression are considered together, as shown in Table 5, 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.

Table 5 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

4 State space models

4.1 Unobserved components in Chornobyl PTSD

A type of observation driven model that is robust to violations of covariance stationarity is the state space model based on the augmented Kalman filter developed by DeJong, and advocated by Harvey, Koopman, and others.

This algorithm, originally developed by Rudolf Kalman, 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.

The process proceeds in phases and the filtering phase involves a process of autoregressive projection 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 iterated until there is complete convergence of the 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.

The model has two 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.

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:

$$\gamma_t = - \sum_{j=1}^{s-1} \gamma_{t-j} + k_t \quad (7)$$

Commandeur and Koopman describe this process in [3, 32-34].

Cyclical components representing between period variations, can be represented by

$$\psi_{1t} = \psi_{t-1}\rho\cos\phi + \psi_{t-1}\rho\sin\phi + e_t \quad (8)$$

$$\psi_{2t} = \psi_{t-1}\rho\cos\phi - \psi_{t-1}\rho\sin\phi + e_t \quad (9)$$

The transition process represents a one-step ahead autoregressive plus a regression on the residuals. 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

$$\alpha_{t+1} = C_t + T_t\alpha_t + R\eta_t \quad \eta \sim NID(0, H_t) \quad (10)$$

$$y_t = D_t + Z\alpha_t + \epsilon_t \quad \epsilon \sim NID(0, Q_t) \quad (11)$$

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

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

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

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.

4.1.1 Male PTSD model

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

$$\begin{aligned} malePTSD_t = & .107 * level + 0.472malePTSD_{t-1} \\ & + 27.35Chornblip + 0.04Chornblip_{t-1} \end{aligned} \quad (12)$$

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 matching of the components with the signal is shown in Figure 11.

Table 6 Male PTSD model

UC(4) Estimation done by Maximum Likelihood (BFGS, exact score)
The database used is Chornts.in7
The selection sample is: 1980 - 2010 (T = 31, N = 1)
The dependent variable Y is: maleptsd
The model is: $Y = \text{Level} + \text{Irregular} + \text{AR}(1) + \text{Interventions}$
Steady state. found

Log-Likelihood is 116.212 (-2 LogL = -232.424).
Prediction error variance is 0.000217059

Summary statistics

	maleptsd
T	31.000
p	3.0000
std.error	0.014733
Normality	11.185
H(9)	0.75095
DW	2.3427
r(1)	-0.24887
q	7.0000
r(q)	-0.021644
Q(q,q-p)	15.798
R^2	0.93111

Variances of disturbances:

	Value	(q-ratio)
Level	0.000135158	(1.000)
AR(1)	0.000106406	(0.7873)
Irregular	1.65619e-11	(1.225e-07)

AR(1) other parameters:

AR coefficient	0.47237
----------------	---------

State vector analysis at period 2010

	Value	Prob
Level	0.10709	[0.00000]

Regression effects in final state at time 2010

	Coefficient	RMSE	t-value	Prob
Outlier 1986(1)	0.27003	0.01327	20.34955	[0.00000]
Outlier 1987(1)	0.04382	0.01327	3.30229	[0.00263]

4.1.2 Female PTSD model

Table 7 Female PTSD model

UC(2) Estimation done by Maximum Likelihood (exact score)
The database used Chornts.in7
The selection sample is: 1980 - 2010 (T = 31, N = 1)
The dependent variable Y is: femptsd
The model is: $Y = \text{Trend} + \text{Irregular} + \text{Explanatory vars} + \text{Interventions}$
Steady state. found

Log-Likelihood is 104.395 (-2 LogL = -208.79).
Prediction error variance is 0.000161657

Summary statistics

	femptsd
T	31.000
p	2.0000
std.error	0.012714
Normality	1.6022
H(8)	1.3075
DW	1.8620
r(1)	0.010808
q	6.0000
r(q)	-0.13973
Q(q,q-p)	5.7465
Rd^2	0.96405

Variances of disturbances:

	Value	(q-ratio)
Level	0.00000	(0.000)
Slope	1.54279e-06	(0.01236)
Irregular	0.000124822	(1.000)

State vector analysis at period 2010

	Value	Prob
Level	0.01117	[0.49070]
Slope	-0.00391	[0.15604]

Regression effects in final state at time 2010

	Coefficient	RMSE	t-value	Prob
Outlier 2008(1)	0.07584	0.01266	5.99211	[0.00000]
Outlier 2009(1)	0.06582	0.01323	4.97352	[0.00004]
chornblip	0.20802	0.01356	15.33557	[0.00000]
chornlevel	0.04032	0.01354	2.97817	[0.00636]

How well this models the female self-reported Chernobyl PTSD is revealed in the following component and signal graph in Figure 12. 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.

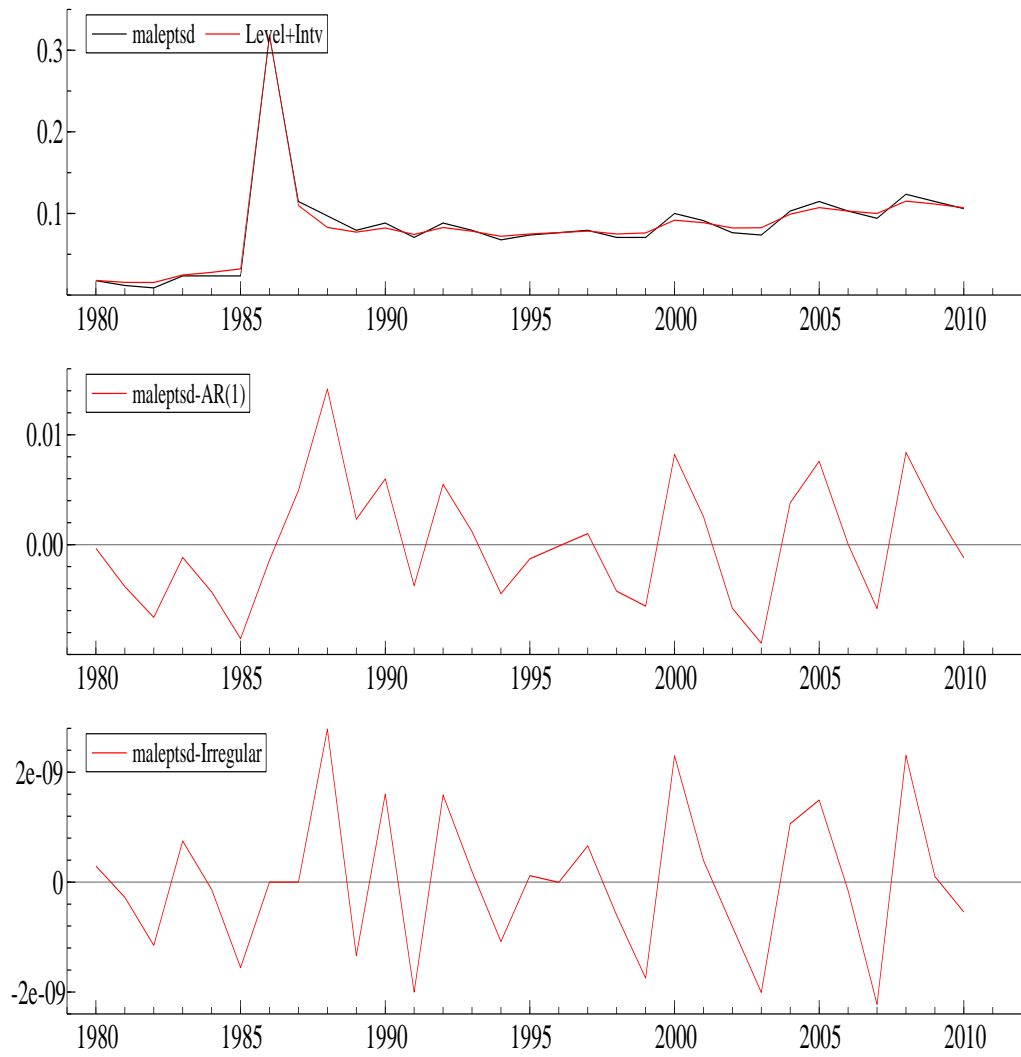


Figure 11: Unobserved components model of male Chernobyl PTSD

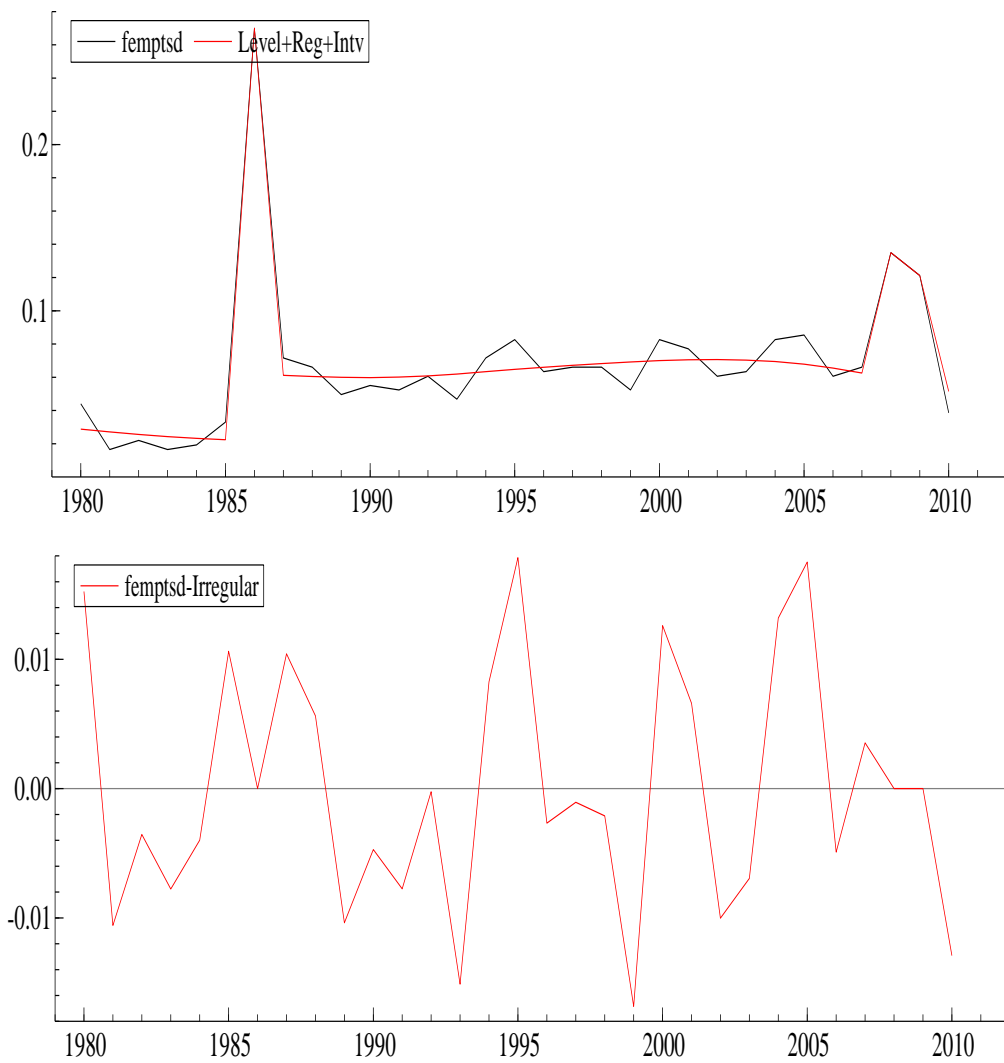


Figure 12: Matching model signal and data in female self-reported Chornobyl PTSD

5 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.

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