

**The Onset of post-Chornobyl Depression among  
Ukrainian residents of Kiev and Zhitomyr Oblasts**

Robert Alan Yaffee  
Silver School of Social Work  
New York University  
6 March 2012

robert.yaffee@nyu.edu edu

# The onset of post-Chornobyl Depression among Ukrainian residents of Kiev and Zhitomyr Oblasts

Robert Alan Yaffee  
Silver School of Social Work  
New York University

6 March 2012

## Outline

1. Introduction: The interview and survey design.
  - Primary objective
  - Survey design
2. Key construct definitions of Level 25 depression
  - Cross-sectional and longitudinal depression
  - Cross-sectional intensity and its distribution
  - Longitudinal person-time of level 25 depression
3. Is there a latency period for such depression
4. Statistical methods: Event history analysis
  - Single episode models
  - Multiple episode models
  - Discrete vs. Continuous time models
  - Fundamental rates and functions
  - Survival, cumulative failure, hazard, and cumulative hazard functions
  - Censoring
  - Event history model assumptions
    - life tables
    - Cox Regression
    - Accelerated failure-time models
5. life tables for depression in males and females

6. single multi-episode Cox regression
  - male depression
  - female depression
7. survey Parametric single and multi-episode AFT models
  - male depression
  - female depression
8. Software
  - The data file : `chcoxstreg1epi4mar2012.dta` the do files : `EHAdepPtsd-gen4feb2012.do`, `chDepstd.pdf`, `stcoxreg.do`.

## 0.1 Acknowledgements

We would like to thank Dr. Mariya Burdina for her valuable assistance with data management, Professor Thomas Borak, and Remi Frazier for his help with dosage reconstruction, as well as Drs. Victor Chtengulov and Gleb Prieb for their help in coordinating and overseeing the interviewing process. We are very grateful to the National Science Foundation for making this research possible with HSD Grant 082 6983.

# 1 Introduction: The nature of this analysis

## 1.1 Primary objective

This is an endeavor to examine depression from self-reports of 703 respondents to a survey conducted in the Ukraine from 2009 through 2011. There have been little, if any, scientific study of the psychological well-being of these residents, because most of the resources available were immediately devoted to studying their physical condition. The dearth of empirical inquiry into the psychological health of the residents leaves a gaping whole in our understanding of what residual psychological sequelae followed this catastrophe. Without scientific study of their psychological well-being, it would not be possible to fully comprehend the aftermath of a nuclear incident.

## 1.2 Survey design

To discover the nature of these residual effects, we conducted a retrospective survey of Ukrainian residents from 2009 to 2012 about the effects of the Chernobyl disaster of April 26, 1986 on their lives. The survey was translated into Russian and back-translated to assure that nothing was to be lost in the translation from one language to the other. Telephone area codes were obtained from the telephone company in the Ukraine and phone numbers were randomly generated by computer to attach to those telephone area-codes. The random digit

dialing procedure assured a representative sample of phone numbers. Up to four call-backs were performed to reach a potential respondent. With assurances of anonymity and confidentiality, informed consent was obtained for an interview at a mutually convenient time and place. The purpose of the study was to examine the psychological sequelae of a nuclear disaster. Many people were uncertain about the effects of the fallout from dispersed radiation. We decided to examine several post-disaster evidence of psychological symptomatology, among which are post-traumatic stress disorder and depression. In this segment of the analysis, we focus on post-nuclear crisis depression. Stata software permits Cox and accelerated failure time regression models to be used in connection with complex survey design. We incorporate our survey research design and sampling weights for our proportional hazards and accelerated failure time regression models.

The longitudinal event history analysis of this phenomenon may help us to better understand the factors contributing to the length of the latency period in the emergence of these symptoms, the shape of the responses to this event, and the risk factors that contribute to the aggravation as well as the buffering factors that contribute to the attenuation of these symptoms in ways that a cross-sectional analysis would not. For it to be able to do so, we need to define the parameters of the symptomatology that comprise the self-reported depression syndrome.

## 2 Cross-sectional and longitudinal depression

Because our sample is a representative sample taken from the population of Kiev and Zhitomyr Oblast, most of the respondents do not exhibit depression. We want to be sure that we are not confusing people who are seriously and substantially depressed from those who might exhibit more mild and occasional expressions of dysphoria.

Over a period of 31 years, since 1980, we asked 702 respondents on a scale of 0 to 100, what percent of depression did they experience each year. In terms of person-years, multiplying 702 times the number of years in the study, we found the overall average level in person-years was at a level of 8.98% with a standard deviation of approximately 23.26%. Most of the respondents-about 83% reported no depression whatsoever. Therefore, the shape of the distribution is zero-inflated. Of course, this distribution is highly non-normal, with the outstanding maximum at zero. To be sure that we were not going to include people with more mild dysphoria among those with serious and substantial depression, we excluded the lower 24% to obtain a truncated distribution of what we call level 25 depression. By dropping the lower standard deviation of the sample, we avoid some of the subjective variation in defining the depth and scope of the state of mind entailing hopelessness, helplessness, and sorrow for the mindset to be called depression. Although in longitudinal studies person-years is a good aggregate measure of the depression.

But if we wanted to extract the time dimension and consider depression at a particular cross-sectional point in time, we would be thinking in terms of

persons reporting depression rather than person-years of depression. But we risk confusing people in a bad mood with persons experiencing depression.

By redefining the distribution as a level 25 depression rather than any level of depression, we move all of those who report levels lower than the 25th percentile, into the zero category. This migration of observations further inflates the zero bin, rendering the distribution even more lopsided and intractable than before. However, if we dropped all of these cases, we would not retain much of a sample, because the zero category is occupied by 87.80% of the male person-years whereas it is now occupied by 84.79% of the female person-years.

In other words, these distributions appear to be zero-inflated and substantially negatively skewed, so that they cannot be considered normally distributed by any stretch of the imagination. We truncate the lower 24% of the distribution to avoid including persons with less intense dysphoria among those suffering from serious and substantial depression. After having truncated this distribution to avoid those problems, the males in the upper and the females in the lower panel of the Figure one display similar and noteworthy patterns, which we call level 25 depression (on a scale of 0 to 100). Although truncation does not restore normality to either distribution, we can begin to examine them in more detail now. When we do we can see some similarities in the reports of the two genders. Both males and females report spikes at the extremes, the midpoint, as well as some clumps of observations at 10% intervals. This may reflect a cultural desire to proffer rounded approximations in an informal discussion with high precision cannot be insisted upon when people are asked to recall things over a 30 year period. Regardless of gender, the histograms of the level 25 depression distributions, shown in Figure one, appear to be remarkably similar.

What happens to the distributions after the transformation that moves the lower 24% of the person-years into the zero category? We can see what happens by examining Table one on the next page.

Table 1. Panel1: Between and within level 25 depression of males

. xttab dep25 if gender==1

dep25	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
0	8727	87.80	330	97.35	87.91
25	12	0.12	3	0.88	13.48
28	1	0.01	1	0.29	3.23
30	239	2.40	60	17.70	18.97
31	7	0.07	1	0.29	22.58
40	143	1.44	49	14.45	11.99
42	1	0.01	1	0.29	3.33
45	1	0.01	1	0.29	3.23
48	1	0.01	1	0.29	3.23
50	300	3.02	87	25.66	12.92
55	1	0.01	1	0.29	3.33
57	1	0.01	1	0.29	3.33
60	38	0.38	25	7.37	5.46
70	60	0.60	34	10.03	6.34
75	6	0.06	3	0.88	6.45
80	59	0.59	29	8.55	8.67
81	1	0.01	1	0.29	3.33
88	1	0.01	1	0.29	3.23
90	20	0.20	15	4.42	4.35
95	1	0.01	1	0.29	3.23
100	320	3.22	80	23.60	15.76
Total	9940	100.00	725	213.86	46.76

(n = 339)

Continued on the next page...

Table 2. Panel1: Between and within level 25 depression of females

```
. xttab dep25 if gender==2
```

dep25	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
0	8954	84.79	361	99.72	84.69
25	2	0.02	2	0.55	4.22
26	2	0.02	2	0.55	3.67
28	1	0.01	1	0.28	3.33
29	3	0.03	2	0.55	5.57
30	370	3.50	85	23.48	15.10
31	1	0.01	1	0.28	3.23
35	1	0.01	1	0.28	3.23
36	2	0.02	2	0.55	3.23
38	1	0.01	1	0.28	3.23
39	1	0.01	1	0.28	3.23
40	113	1.07	50	13.81	8.32
43	1	0.01	1	0.28	3.23
44	1	0.01	1	0.28	3.23
48	1	0.01	1	0.28	3.33
50	296	2.80	117	32.32	8.98
51	1	0.01	1	0.28	3.23
53	1	0.01	1	0.28	3.33
55	6	0.06	1	0.28	19.35
57	3	0.03	3	0.83	3.63
60	101	0.96	34	9.39	10.16
63	1	0.01	1	0.28	4.00
65	3	0.03	2	0.55	5.23
66	1	0.01	1	0.28	3.33
67	1	0.01	1	0.28	3.33
70	76	0.72	37	10.22	7.13
75	19	0.18	1	0.28	61.29
77	1	0.01	1	0.28	3.33
80	84	0.80	38	10.50	7.72
90	41	0.39	18	4.97	9.03
100	471	4.46	88	24.31	18.51
Total	10560	100.00	857	236.74	42.24

(n = 362)

Although the overall columns report person-years, in a panel tabulation, the between frequency reports the number of persons, and we can observe how much more clumping occurs in the zero category as a result of the migration. However, the objective is to compare the remaining clumps of observations, so we temporarily remove the zero category, so that we can observe how the relative size of the residual clusters compare to one another. We can now examine the relative sizes of these clusters in the Figure one and while we obtain a more objective assessment from their summary statistics contained in Table three below.

If we examine the summary statistics of these two person-year distributions in Table one, we find that the means are quite different from their midpoints and the skewness deviates from what would be expected of a normal distribution. Nevertheless, the males exhibit a slightly lower mean level 25 depression and a

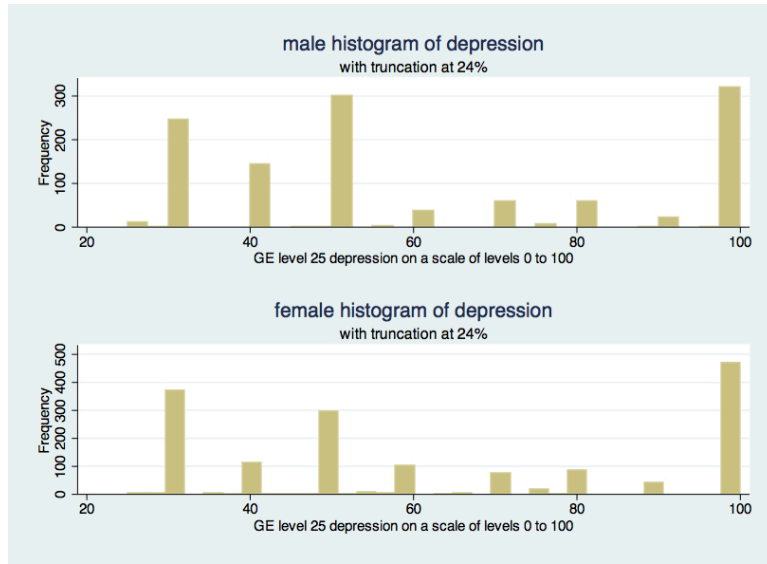


Figure 1: Figure 1: distributions of depression above 24% by gender

slightly smaller variance than that of the women. It is interesting that among those with valid non-zero level 25 depression scores, the average for men is approximately 61.4% while the mean for women is about 63.7%, both of which are at least ten percentage points above 50% but about as large as the new midpoint of the range of the newly truncated distribution.



**Table three: Distributional summary statistics of level 25 depression by gender**

. -> gender = 1. male

GE level 25 depression on a scale of levels 0 to  
100

	Percentiles	Smallest		
1%	28	25		
5%	30	25		
10%	30	25	Obs	1216
25%	40	25	Sum of Wgt.	1216
50%	50		Mean	61.40296
		Largest	Std. Dev.	27.03974
75%	100	100		
90%	100	100	Variance	731.1478
95%	100	100	Skewness	.3897826
99%	100	100	Kurtosis	1.58884

-> gender = 2. female

GE level 25 depression on a scale of levels 0 to  
100

	Percentiles	Smallest		
1%	30	25		
5%	30	25		
10%	30	26	Obs	1606
25%	40	26	Sum of Wgt.	1606
50%	55		Mean	63.74533
		Largest	Std. Dev.	27.73835
75%	100	100		
90%	100	100	Variance	769.4161
95%	100	100	Skewness	.190763
99%	100	100	Kurtosis	1.458249

By examining the distribution without such a truncation will reveal a zero-inflated distribution, where most of the respondents do not report any depressive symptomatology at all. In light of this fact, the cut-off of the lower 24% of the distribution no longer seems so large. However, real advantages appear in the analysis when the dimension of time is included.

### 3 Statistical Methods: Event History Analysis

#### 3.1 single transition models

Event history or survival analysis begins with the life table, which describes a single transition from the time of origin until the time of an event till an event. The event, which can be a death or some sort of failure, can be the lapse into an illness, such as depression or PTSD, or a recovery from it. With discrete time models, there are predefined fixed-intervals of time during which an assessment is made. For each of these intervals of time during the single transition an accounting is made of the number of patients or respondents entering, the number experiencing the event, as well as those who are lost to follow-up during that

interval. Accordingly, proportions are tallied in terms of the *survival*, *hazard*, and *cumulative hazard* rates. When there is one transition, this is usually called a single episode analysis.

When event history analysis was originally developed, the survival time was the time from diagnosis until the time of the death. Consequently, these terms are used somewhat interchangeably in such analysis. We are measuring the time from 1980 until their first reported spell of depression as the time to the event or failure-event or death as it were. Because the study is retrospective, right-censoring does not take place until the end of the study, when the interview took place. As instantaneous definitions were refined, the intervals no longer had to be equal, and continuous time survival analysis became possible. Nonparametric life tables may be used to analyze single transition models or groups of them.

### 3.2 multiple transition models

It is possible for event history analysis to be applied to situations where there are repeating events, sometimes called multiple transition or multiple episode analysis. Multi-episode analysis is based on a transition specific hazard rate. One example of multiple episode analysis is a study of employment. A person may hold several jobs over his employment history. In a relapse analysis, a person with a drug, gambling, drinking, or recidivist problem may undergo several relapses before being cured. Each relapse can constitute another transition. The research problem is how to analyze event histories with multiple transitions.

One solution is to analyze each episode separately. We can analyze the time until the first event, the second event, and so on. Perhaps before doing this, we ought to determine whether the survival or hazard rates are significantly different depending upon the number of episodes under examination. The types of episodes may be grouped according to the number contained and their separate survival curves may be tested for equality under the null hypothesis. If those rates are not significantly different, they may be pooled and treated as one process [? , 85].

If the curves significantly differ depending upon the number of episodes in the analysis, nonparametric methods have limited utility. They cannot accommodate covariates, much less time-varying covariates. There may be unobserved time dependence or unobserved heterogeneity of the phenomenon in which case it behooves the researcher to apply parametric transition rate models that takes into account these differences[? , 86].

Transition rate models, estimated by maximum likelihood, and assuming time independence, can accommodate covariates such as duration dependence, number of spells, and other covariates that may explain the transition rate. An exponential model which assumes equality of transition rates can be used as a baseline against which to compare other models. It can accommodate time-constant, which are fixed at the beginning of the episode, or time-varying covariates as needed. For each of the transitions a separate model is applied. The covariates can be spell-constant or spell-varying.

A more cumulative approach to multi-episode models uses the same starting

time as the beginning of the study for all analysis. The analysis is transition rate specific in that it focuses on one transition at a time. The transition rate is assumed to depend on the time spent in the episode and distribution of the duration time of the episodes is assumed to be independently and identically distributed. One of the covariates may be the number of spells preceding the onset of the spell under analysis because in a transition specific analysis, as is the case with Markov and semi-Markov models, the analysis of a particular state is always based on the state space history preceding it. Because the transition rates are i.i.d. in a multi-episode model, different models may be used for different transitions from the starting point in time to the onset of the spell under examination [3, 62-64].

### 3.3 Discrete time vs Continuous time models

Event history models entail a transition from one to another state. A state may be a condition of being non-depressed. The destination state may be a condition of being depressed. Thus, a transition from the original state to the destination state may describe the process under consideration. Most transitions from one state to another do not occur like Presidential elections at fixed intervals. Although discrete time models, structured as panel data, have simplicity as an advantage, where a psychological transition is usually divided into a few clearly defined fixed time intervals during which the process is analyzed by an analysis of proportions where the denominator is generally some measure of time. When using discrete time models, we are generally dealing with fixed-interval analysis, and the incidence rate is often used. Matusner and Bahn define the incidence rate as "the number of persons experiencing the disease divided by the population at risk over a period of time [11, 44]."

However, in real life, psychological transitions are not so structured. Marriages, job changes, lapses into depression or PTSD can and often take place at any point on a time arrow rather. Because continuous time models, the intervals are defined in terms of derivatives, computed at the limit of the time interval as its duration approaches zero, permit more precise time measurements between any two points along the time arrow within the period of observation[13]. They can be adapted to more complicated types of transitions which can take place at any time. Similarly, instead of using incidence rates, we can use prevalence rates, which Matusner, Bahn, and Kramer define as "the number of existing cases of a disease over the total population at a point in time[11, 44]."

For these reasons, we employ continuous time models and methods, which are more realistic and appropriate for the kinds of transition that we find of interest[19, 82-84].

### 3.4 Fundamental rates and functions

There are four fundamental rates and functions essential to the theory of event history analysis. We briefly review them here to help understand the latency period of post-Chornobyl depression. They are the survival rate, the cumulative failure rate, the hazard rate, and the cumulative hazard rate. The survival rate

is the probability of surviving beyond some temporal point in time,  $t$ . When these rates are plotted against time, they become functions of time. Because in event history analysis rates are functions of time, rates and functions are used sometimes as synonyms.

If  $T$  is a non-negative random variable which defines the time from the beginning of a study until the onset of an event, we can define the probability density function of it as  $f(t)$  and its cumulative distribution function as  $F(t)$ .

### 3.4.1 *The Survival function*

The survival function,  $S(t)$ , can be expressed as the complete of the cumulative rate of a death or failure event, such that

$$S(t) = 1 - F(t) = Pr(T > t). \quad (1)$$

### 3.4.2 *The cumulative failure function*

By rearrangement, we obtain the formula for cumulative failure rate

$$F(t) = 1 - S(t). \quad (2)$$

### 3.4.3 *The hazard function*

Before we discuss the hazard function, which is called the conditional probability of failure, we will consider the unconditional probability of failure, which is the probability density function of failure. The probability density function of failure is simply the derivative of the cumulative failure function.

If we were using fixed time intervals for our computations with which we were performing discrete time analysis, Elisa T. Lee [10] describes the probability density function,  $f(t)$ , in such a context when there is no censoring (which we will discuss in the next section) as

$$f(t) = \frac{(\text{number of patients dying in time interval beginning at time } t)}{(\text{number of patients})(\text{time interval})} \quad (3)$$

However, much of event history analysis allows its time intervals to be random. For that kind of analysis, instantaneous formulations of the cumulative failure rate are preferred. In these cases,

$$f(t) = \frac{dF(t)}{dt} \quad (4)$$

which can be taken as an instantaneous rate as the length of the time interval approaches the limit of zero.

$$= \lim_{\Delta t \rightarrow 0} \frac{\text{Prob}(a \text{ person experiencing failure event in interval}(t, t + \Delta))}{\Delta t} \quad (5)$$

In other words, this is the instantaneous failure rate, which needs to be distinguished from the cumulative distribution function,  $F(t)$ . The instantaneous failure rate,  $f(t)$ , can be further expressed as

$$f(t) = \frac{dF(t)}{dt} = \frac{d(1 - S(t))}{dt} = -S'(t) \quad (6)$$

which sums up the relationship between the survival probability and the probability density  $f(t)$  of the failure event [4, 7].

Much of event history analysis however, is based on the hazard rate or hazard function,  $h(t)$ , also known as the conditional probability of the failure event. Expressed in layman's language, the hazard rate is the probability of a failure event, given that the person has survived long enough to be deemed to reside within the risk set, subject to that event. The hazard rate can be formulated as

$$h(t) = \frac{f(t)}{S(t)}. \quad (7)$$

When the hazard rate entails discrete time analysis in fixed time intervals, it is assumed that censoring is randomly distributed, so the median is considered to be a reasonable estimate of the amount of censoring taking place during that interval of time. Therefore, an adjustment is made to the risk set, which comprises the number of people susceptible to experiencing the failure event at that interval of time. This adjustment is an effort to account for those amount of censoring that was not observed. By subtracting one-half of those who died during that interval, this reduction in the size of the risk set is an attempt to make an adjustment for the amount of unobserved events that are assumed to have taken place. Accordingly, Eliza Lee formulates the hazard rate with this adjustment in the discrete time fixed interval context defines as

$$h(t) = \frac{\# \text{ patients dying in interval}}{(\# \text{ patients surviving till interval}) - 0.5 * (\# \text{ patients dying in interval})} \quad (8)$$

### 3.4.4 The cumulative hazard function

But survival analysis would not be complete without more consideration of the the cumulative hazard rate. The hazard rate is defined as the conditional probability of the failure event, which a ratio of the probability of a failure event (potentially entailing morbidity or mortality), divided by the probability of surviving long enough to be part of the risk set of that event. In our study, the hazard rate is the conditional probability of experiencing and reporting depression, conditional upon recalling it after the beginning of 1980. Therefore, the hazard rate,  $h(t)$ , can be expressed as

$$h(t) = \frac{f(t)}{1 - F(t)} \quad (9)$$

The cumulative hazard rate,  $H(t)$ , is the integral of the instantaneous hazard rate. Because we know by definition,

$$\int \frac{dx}{x} = \ln|x| + c \quad (10)$$

it follows that

$$H(t) = \int_0^t h(t)dt = \int_0^t \frac{f(t)}{1 - F(t)} = -\ln[1 - F(t)] = -\ln[S(t)] \quad (11)$$

If

$$\begin{aligned} -\ln[S(t)] &= H(t) \text{ and} \\ S(t) &= \exp[-H(t)] \end{aligned} \quad (12)$$

then

$$S(t) = e^{-\int_0^t h(t)dt} \quad (13)$$

But some researchers who study multi-episode data may prefer to examine the cumulative hazard function. From equation 11, Nelson and Aalen noted that this function could be as

$$H(t) = \sum_{i|t \leq t} \frac{d_i}{n_i} \quad (14)$$

which is really the number of failures at each observed time divided by the number at risk at that time. When these are added up over the study time, we get

the Nelson-Aalen estimator. Aalen in 1978 recommended that the asymptotic standard error be computed from the variance of the estimator, given by

$$Var(\widehat{H(t)}) = \sum_{i|t \leq t}^t \frac{d_i}{n_i^2} \quad (15)$$

whereas the confidence intervals are taken from  $H(t)exp(z_\alpha/2 * sqrt(\psi))$ , where

$$\psi^2 = \frac{\widehat{Var}(\widehat{H(t)})}{\widehat{H(t)}^2} \quad (16)$$

Details as to this formulation may be found in [4, 109].

### 3.5 Censoring

One of the fundamental constructs of event history analysis pertains to the censoring of data. Censored data are those data that which may entail a failure event that cannot be known by us. There are three situations that entail drop-out, loss to follow-up, or study termination preceding process time. Drop-out may take place if a patient or respondent moves to another location, becomes temporarily ill, or is incarcerated. He may for an interval of time disappear from those responsible for patient monitoring. As for loss-to-follow-up, a patient may become unavailable after the study cut-off. He or she may not have experienced the depression or PTSD prior to the study termination. We do not know whether they have experienced it later. They are lost-to-follow-up and may be treated as censored, accordingly. There are protocols for accounting for data Under such circumstances, so we should be clear about what is meant by censoring and how we handle these phenomena if and when they can occur.

There are several codifications of censoring. One of these depends on whether the censoring pertains to fixed intervals or random intervals. Censoring with fixed time intervals is called type I censoring, whereas censoring with random time intervals is called type II censoring. Fixed interval analysis is often called discrete time event history analysis or even panel data analysis [9, 40-41].

Random censoring assumes that the time till the event and the censoring time are independent of one another [12, 6]. If the censoring within an interval is random, the midpoint represents a reasonable estimate of central tendency of the amount of censoring within that time interval.

Another codification of censoring is based on the direction of the censoring. Imagine that the arrow of time extends from some point of temporal origin on your left to some temporal destination on your right, as does the time axis in Figure 2, so the arrow of time goes from left to right. *Left-censoring* occurs when the entry time may preceded the beginning of the observation time. It is possible that an event can occur before it can be observed but because we did not observe it we cannot say for sure that it happened. *Right-censoring* occurs

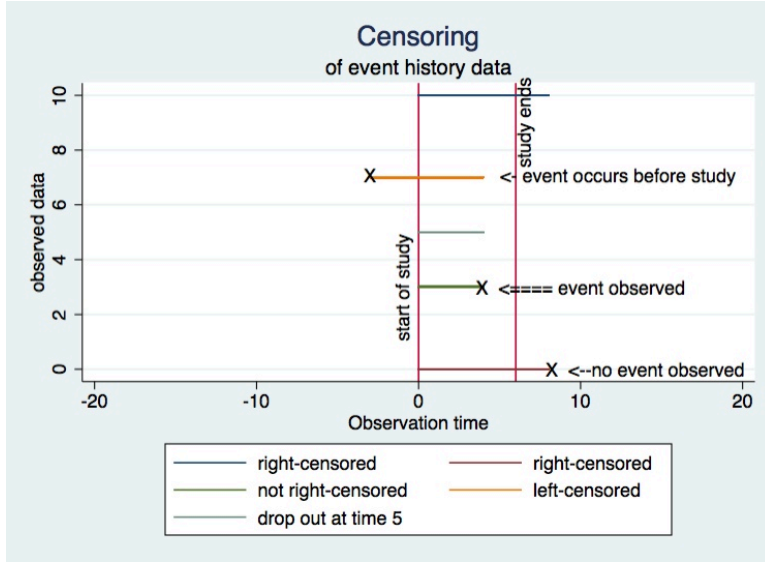


Figure 2: Censoring of data

when a failure event can take place after the observation time is terminated. Right censoring can also occur if no observation of the event takes place during the study time although that study time continues after the observation period ends. Right censoring can also occur due to drop-out of the respondent, who may have moved away, been incarcerated, or kidnapped. *Interval censoring* occurs when the event can occur either before or after observation time. If both right and left censoring can occur, interval censoring takes place. Figure 2 illustrates these forms of censoring with a line graph.

Censoring can come about when the event of interest cannot be observed because of drop out, loss-to-follow-up, or temporal termination of the study preceding a possible failure event. Loss to follow-up stems from when a person cannot be found for determination of his condition. He may have moved away or may have been incarcerated such that his whereabouts becomes unknown to the researchers. Alternatively, the patient may experience adverse side-effects from participation that he drops of the study. Even if the researchers are aware of his whereabouts, he may decline to continue with the protocol. Cohort studies that follow patients over time are expensive. Cost-factors require study termination before the final condition of the patient or respondent can be determined. Under such circumstances, a failure event could occur along the arrow of time to the right of the study termination time. If study termination can precede the occurrence of a failure event, then right-censoring can take place. Because our study is retrospective from 1980 and that beginning of the study time is the same for all respondents, there is no left-censoring of the data[12, 5-6].



### 3.5.1 Censoring in single episode models with one transition rate

We examine the latency period of the disorder first. We begin by asking people about their health prior to the Chernobyl disaster on 26 April 1986. We commence this retrospective study period at January 1, 1980 and proceed until the end of 2009. Therefore, the retrospective study time covers 31 years of recall. The question posed was about previous nature of emotional responses to events. The time frame of the study begins in 1980 in order to provide us with several years of pre-disaster experience against which the respondents can compare their post-Chernobyl emotional responses to events. It is well known that bias may be introduced into the study the further back a respondent has to remember phenomena in order to answer questions posed. Therefore, we do not ask for particular dates, but rather in this analysis we ask for the year, and, in another analysis the period, in which events occurred. In that other analysis, the periods or waves cover the period of 1986 following Chernobyl, a decade thereafter, and the time up to the end of 2009, since the end of that decade. Thus, people who cannot remember exact years may be interviewed in such a manner as to yield useful data.

By focusing on the latency period, which we call the time until the onset of symptoms, we can examine the transition rate or time delay pattern before the appearance of the syndrome under consideration. Some people do not exhibit the symptoms by the time the study termination. We do not know whether they do or do not experience those symptoms and they are lost to follow-up. If we have not observed the depression by the end of the study period, these respondents are **right-censored**. Other people exhibit a clear pattern of delay before onset of depression or PTSD and we observe this before the end of the study. Although there is censoring in the former case, we observe no censoring in the latter case. We need to be clear about the censoring under these circumstances understand in order to deal properly with it [2, 17].

### 3.5.2 Censoring with multiple episode models, subdivided into separate transition rates

Multiple episode models can be segmented into several single transition rate models, in which each transition rate is modeled separately. A dummy covariate could indicate whether there were relapses before the final destination state. Respondents experiencing no depression before the end of the study period would be **right-censored**. These models share the characteristics of the single transition rate models described above.

### 3.5.3 Censoring in multiple episode models with several transition rates

Some persons may experience a single spell of depression whereas others may experience a series of spells or relapses. Persons in danger of relapse have been called borderline. We will examine the number of people exhibiting one spell of depression as well as the number experiencing multiple spells of the same

disorder. From an analysis of the data, we can see that some individuals report multiple episodes of depressive symptomatology.

Suppose we are only what Yamaguchi calls one-way transition models. These models focus on unidirectional transitions—from non-depression to depression with multiple spells of depression. One way to do this is always to use the starting time of the study as a reference point. We can separate focus on different destination states. The first destination state might be the onset of spell one of level 25 depression. The second analysis will focus on the onset of spell two, etc. For each analysis, the duration of time from the starting point to the destination point will be a covariate. Other covariates include the previous spell number, the duration of the previous spell, and the number of intervening spells, along with the average percentage of intensity of the previous spell. Moreover, for each analysis, those who have not experienced the failure event by the end of the study time are deemed to be **right-censored**.

Because our study is retrospective, there is no left-censoring in the data. All recollections are collected as of January 1980.

In two-way transition models, censoring may be more complicated. One transition would be from the nondepressed to the depressed state. The other transition would be from the depressed to the non-depressed state. The first transition is depression-directed, whereas the second transition is recovery-directed. The origin state of the first transition is that of the non-depressed condition and the destination state of the first transition would be the onset of the first depressed state. The origin state of the second transition would be that of depression and its destination state would be that of recovery or non-depression. In a two-way transition model, each direction would have its own equation. The complete system could have an equation for each transition.

Respondents who do not arrive at the destination state by the end of the study would be censored.

From these data, we will be able to compute the survival probability, the hazard rate, as well as the cumulative hazard rate for males and females and to graph them for our inspection.

By using the hazard rate as an endogenous variable in a semi-parametric regression model, we can develop a model of what variables contribute to explanation of the hazard rate, or the conditional probability of depression, under the assumption that all of these respondents were susceptible to it. The model should provide us with insights as to the risk and buffering factors regarding post-nuclear event depression.

Using the natural log of time since 1980 or the incidence of Chernobyl, we may obtain an understanding of a baseline against which to compare post-Chernobyl events. Accelerated failure time models may provide a more precise analysis of the depression aftermath of this nuclear disaster.

### 3.5.4 Event history model assumptions: Nonparametric event history analysis

Nonparametric survival analysis uses one or another of these fundamental rates and functions to examine groups or to compare groups against one another. This can be done in fixed-time intervals or in continuous time. Whether we use an actuarial life table or a Kaplan-Meier continuous time version of such a table, we need to decide whether we will analyze one transition or episode at a time, or multiple transitions at one time—which is sometimes referred to as multi-transition or multi-episode data, as well as how we are to handle events we may not have observed, which we refer to as censored data. Single transition data consist of the move from one state to another state in space and time. When we examine the movement between one state to another, Tuma and Hannan call this a binomial model. If there were a possibility of multiple destination states, they refer to the model as a multinomial model[19, 92]. Our examination of level 25 depression and PTSD are treated at first as single transition binomial models in which there is a transition from the original state to a state of succumbing to depression or PTSD. The description of this process provides a good basis upon which to begin an analysis.

But Tuma and Hannan (1984) maintain that they possess other properties that might permit them to be classified as Markov or semi-Markov models. Markov models are models in which the current state depends on the state immediately preceding it. They also maintain that the Markov models exhibit time stationarity (with a stable mean and variance and autocovariance), whereas semi-Markov models assume that their transition rates depend on duration in the previous state, length of time since that previous state, as well as on chronological time so that they tend to be more realistic than the conventional Markov model[19, 94-95][22, 54]. We can specify our multi-episode models to include these covariates.

For example, the nonparametric life table, decomposes each unit interval in the study into the size of the risk set, the number of failure events, the number censored, the survival probability, its standard error, and confidence interval. The censoring time and the duration time are assumed to be independent of one another, so the censoring can be randomly distributed. In other words, there should be no time dependence with respect to censoring. This structure fits our data as it was collected in yearly intervals. The nonparametric life table generally assumes that there is homogeneity of the population across the time intervals and that the failure density rate across the intervals is generally the same and normally distributed. We test these assumptions and find that the groups when broken down by gender as well as age are significantly heterogeneous.

Although we begin our analysis with a simple actuarial life table to describe survival probability by life table, we progress to continuous time Kaplan Meier analysis to refine our comparative analysis by gender and age group.

Thus, the variance and asymptotic standard errors of the survival function can be estimated accordingly. If one allows for multiple episodes, usually the

same size of the episodes will vary, resulting in substantial population heterogeneity. The way around this is to separately analyze a specific number of episodes at one time.

In 1958, Kaplan and Meier are credited with a survival analysis decomposition by which

$$\widehat{S}(t) = \prod_{i|t_i < T} \frac{(n_i - d_i)}{n_i} \quad (17)$$

where  $d_i$  indicates the number of who have failed and  $n_i$  designates the number at risk of failure[18, 415]. At each interval the numerator is reduced by the number of experienced the failure event. The resulting proportion is the survival probability for that interval. In other words, the proportion not experiencing the event is the survival probability, which is multiplied by the probabilities corresponding probabilities at each of the intervals to obtain the cumulative survival probability. When this is plotted against time, we have the survival function. This function may differ from one group to another. When they are compared, they can reveal much about the likelihood of not failing over time. Confidence intervals are used based on the asymptotic variance of  $\ln[-\ln\widehat{S}(t)]$  which is based on the following formula:

$$\hat{\sigma}^2(t) = \frac{\sum \frac{d_i}{n_i(n_i - d_i)}}{(\sum \ln \frac{(n_i - d_i)}{n_i})^2} \quad (18)$$

However, if sampling weights are applied this formula is no longer appropriate. If Greenwood's formula for standard errors is applied to the Kaplan-Meier product limit survival estimates, that formula is taken from the square root of

$$Var(S) = S^2(t) \sum_{i|t_i \leq t} \frac{d_i}{n_i(n_i - d_i)} \quad (19)$$

using the same definitions of the letters as those given above[18, 415].

Asymptotic standard errors allow us, if the groups are not too heterogeneous, to compare them to one another, in order to ascertain which group is likely to succumb to failure. We can also employ compute the hazard, incident rate, or conditional probability of failure at any point along the continuum of recorded history to compare the groups. Alternatively, we can compute smoothed estimates of the hazard rate, or even the cumulative hazard rate using a Nelson-Alen estimator for cumulative hazard. For our analysis, we employ the nonparametric life table and Kaplan-Meier analysis to describe the data, before we begin modeling with the use of our sampling weights.

### Multiple episode analysis

Eventually, we will later proceed to examine multiple transition, repeatable event data. We can examine each transition separately, or we can restructure the data so that one episode follows another and that a person can experience multiple transitions from a state of non-depression into a state of level 25 depression. For such an analysis, the episode of the ailment, failure, or death must have a spell sequence number, which we call a spell number or spell id. To distinguish one person's sequence from others, each respondent must have his own id number. All other identifying information is stripped from the file to protect his or her anonymity and confidentiality. A state variable is also constructed, so we can distinguish between one and two-way transitions. With this variable, we can determine whether we are analyzing the transition into or out of the failure event. Given the time and resources, we might find that a two-way analysis would reveal much about recovery and therapeutic methods.

#### 3.5.5 *Cox Regression models*

The Proportional hazards (Cox) regression analysis uses the odds ratio of the hazard rate divided by 1 minus the hazard rate as a dependent variable in a logistic regression model[22, 15-41]. These models assume that the baseline hazard rate is not a matter of concern. The advantage of this model is that we need not worry about the baseline hazard rate or its distribution[4, 129-131]. The semi-parametric regression models avoid specification of the the distribution of the transition rate as as much as possible, while allowing for the influence of covariates. They are particularly useful when the magnitude and the direction of the effect of the covariates is the concern, with little knowledge of the nature of the residual distribution involved.

$$\ln \left( \frac{h(t)}{1 - h(t)} \right) = \beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_k z_k \quad (20)$$

We convert the denominator to a constant

$$\ln \left( \frac{h(t)}{h_0} \right) = \beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_k z_k \quad (21)$$

Then we antilog both sides of the equation to obtain

$$h(t) = h_0 \exp(\beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_k z_k) \quad (22)$$

Proportional hazards regressions are logistic regressions that assume proportionality of the hazards. In other words, these regression models assume that there is no significant interaction between the covariates and the process time. The Schoenfeld residuals can be used for testing the proportional hazards

assumption[4, 212]. When the effect of time is controlled, the odds are presumed to be stable over the process time [2, 233-235].

Frank Harrell Jr (2002) also notes that the Cox regression model assumes linearity and additivity [7, 477-493].

Other residuals useful for diagnostics of the Cox model are the Cox and Snell residuals for model fit, the Martingale residuals for functional form, and the deviance residuals for assessment of outliers[4, 212].

If the proportional hazards assumption is violated, it may be possible to estimate a stratified or conditional models if the covariate in question can be collapsed into a factor of several levels. Cox regression models focuses on the effects on the hazards of the covariates.

### 3.5.6 Accelerated failure time models

Other parametric transition rate models use as a dependent variable the natural log of the time till a failure event. These models focus more on the analysis time. These models employ different distributions to fit the model. When the transition rates are more or less constant over time, we can use the exponential model for estimation. If the transition rate are monotonically increasing or decreasing we can use the Gompertz, the Weibull distribution models for estimation, and when the transition rates change over time, we can try to estimate the loglogistic or the lognormal models [? , 183]. The advantages of these models are that they can accommodate covariates and time-varying covariates. They are useful for prediction and they may also be adapted to accommodate individual frailty (random effects) or shared frailty(grouped random effects).

$$\ln(t) = a + b_1x_1 + b_2x_2 + \dots + e_t \quad (23)$$

AFT models are harder to fit than proportional hazards models, but if they can be fit, they often can give better predictions. Model building with nested models may be performed by likelihood ratio tests with preference being give to those models with the highest log-likelihood or the lowest information criterion. We may wish to test for frailty to represent heterogeneity or random effects.

AFT models assume that the proper distribution of the model is known. They assume homogeneity of the error. They assume linearity and additivity.

## 3.6 Covariates

The covariates can be time-constant covariates within a single episode transition analysis. Alternatively covariates may be some version of a time-varying covariate. If the covariates are time-varying, they may be spell constant or spell-varying. Time dependent covariates may be parallel processes operating at the same or different levels– for example, the individual level, the organizational, or the macro-systemic level. They may operate within different subject domains on the same level, or they may be combinations of the foregoing. They may interact with one another as well[? , 120-121].

Historical or social change may generate time dependent processes that are best measured by time-varying covariates. Cohort effects may generate other changes in individuals that are best measured by time-varying variables. Age and experience may bring about period shifts in explanatory variables in some of the models. There are many reasons to use an analysis that supports time-varying covariates[19, 186-264].

## 4 The time till onset of depression

### 4.1 The single transition rate model

Our first analysis is a single transition or single episode nonparametric analysis. At the outset, we wish to analyze our sample without making many assumptions about its composition or structure. Our starting point in time is the beginning of the study, as respondents recalled their health during the year of 1980. We study the time it takes until the first transition from the origin state of health into the destination state, whether it be one of depression or one of non-depression. In a semi-Markov model, we can observe the transition probabilities from one state into another. The condition of the Chornobyl disaster surely affected some of the respondents living closer to Chornobyl more than other living farther away.

Some respondents may experience depression prior to the advent of the Chornobyl disaster. Others did not. We will pay close attention to the survival probability, the probability of not experiencing depression prior to the accident and compare it to the survival probability after the accident during this first transition to the onset of the state of depression. We will be interested also in the proportions before and after Chornobyl to see whether there is a significant difference between them, if we assume that the transition probabilities are independent and identically distributed.

Some researchers or scholars may wonder whether geographical proximity or the residence or workplace of the respondent to the accident site can govern the residential may determine whether the respondent can be considered in the control or experimental group of a quasi-experimental design. We argue that our primary objective was to obtain a representative sample from which we could responsibly generalize our findings to the population at large. Without our ability to do that, our study would be devoid of external validity. To do so, we had to conduct a random digit dialing protocol which restricted our outreach to respondents at the other end of the phone numbers that we randomly selected. This process was undertaken after more than 20 years after the catastrophe that was Chornobyl. During that period of time, many persons were relocated or moved on their own to outer reaches of the Ukraine or even to other countries within Europe or beyond to the the middle East and the West. We could not and would not wish to subject them to continued habitation within a contaminated or semi-contaminated environment. Our objective is to learn all that we can from this tragedy to see how it affected the population at large, and to try to find ways to prevent its recurrence, as well as to do what we can to alleviate the

suffering of those caught up in the maelstrom of events by committing ourselves to a completely honest and candid exposition of our analysis whatever its results may be. Although our investigation concentrates on the representative sample of the population, it is not meant to downplay the very real needs or complaints of those who have suffered from more exposure to the radiation or fallout.

Adherence to this protocol generated a sample of respondents located largely in the Kiev Oblast with many people living at a comfortable distance from the site of the disaster. The findings from such a representative sample may not emphasize the experiences of those who suffered from heavy exposure to radiation or fallout, and are by no means intended to belittle them by giving emphasis to those who may not have suffered so much. A very small percentage of our respondents reported living near the accident site and is not meant to divert the serious attention and support that they need and deserve.

### *Level 25 Depression*

When we examine the survival probability— which is the probability of not experiencing the failure event of depression— we first examine some basic characteristics of our sample. We find that more women than men lapsed into depression. Of our sample of 702 respondents, consisting of 339 men and 363 women, 146 (48.29%) males and 168 (51.71%) females experienced the onset of a spell of level 25 depression. We measure depression on a scale of 0 to 100, and if we drop the lower one standard deviation to reduce uncertainty due to natural variance of individual subjective evaluation, we obtain a level 25 depression, which means that on that scale, the depression we evaluate is at least 25% intense.

When comparing the number of respondents at risk with those experiencing the level 25 depression, the incident rate for the whole sample was 0.081. When the sample was broken down by gender, the males and females had approximately the same incidence rates. For the males it was 0.080 whereas for the females, it was 0.0802.

In table four on the next page, the first two columns on the left of the table represent the interval of one year from January 1980 when the recollection time began. The beginning total are the number of respondents at risk of experiencing the first spell of level 25 depression. The deaths represent the failure event of becoming depressed at least at level 25. The survival probability is computed as the  $1 - \text{the cumulative failure rate}$ . That is the ratio of those experiencing the depression event (indicated as the number of deaths) in that interval to those at risk of dying. Hence the survival probability for the first interval equals  $1 - 2/154 = 0.9870$ . There is no loss to follow-up as this is a single transition analysis. Greenwood's formula is used for the standard error and the formula for this can be found in equation 19 above. This table presumes no loss due to censoring. A graph of this survival function can be found in Figure 3 below.

At the bottom of Table 4, panel 1, we can see that there are a few net losses recorded. These losses are due to censoring of a few observations where events were recorded during the same year as the interview. Such cases are considered censored. When we employ the continuous time analysis, owing to



its increased accuracy, we observe no loss of cases till the end of the transition where the onset of depression takes place due to the retrospective nature of this study. For this reason there are a few net losses recorded near the end of the study, shown in panels one and two, for both men and women. These are usually due to the few cases where depression was ongoing in the same year as the interview took place.

**Table 4 Panel 1: Life table of survival probability of time till level 25 depression**

For males:

Time	Beg. Total	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf. Int.]	
1	154	2	0	0.9870	0.0091	0.9491	0.9967
2	152	4	0	0.9610	0.0156	0.9153	0.9823
3	148	3	0	0.9416	0.0189	0.8907	0.9692
4	145	1	0	0.9351	0.0199	0.8827	0.9645
5	144	5	0	0.9026	0.0239	0.8436	0.9401
6	139	39	0	0.6494	0.0385	0.5684	0.7189
7	100	8	0	0.5974	0.0395	0.5155	0.6700
8	92	7	0	0.5519	0.0401	0.4700	0.6264
9	85	8	0	0.5000	0.0403	0.4187	0.5758
10	77	8	0	0.4481	0.0401	0.3683	0.5245
11	69	1	0	0.4416	0.0400	0.3621	0.5180
12	68	2	0	0.4286	0.0399	0.3497	0.5050
13	66	6	0	0.3896	0.0393	0.3127	0.4657
14	60	2	0	0.3766	0.0390	0.3005	0.4525
15	58	1	0	0.3701	0.0389	0.2944	0.4458
16	57	5	0	0.3377	0.0381	0.2642	0.4125
17	52	5	0	0.3052	0.0371	0.2344	0.3787
18	47	7	0	0.2597	0.0353	0.1934	0.3308
19	40	4	0	0.2338	0.0341	0.1704	0.3030
20	36	5	0	0.2013	0.0323	0.1422	0.2679
21	31	4	0	0.1753	0.0306	0.1201	0.2393
23	27	3	0	0.1558	0.0292	0.1038	0.2175
24	24	2	0	0.1429	0.0282	0.0931	0.2029
26	22	5	0	0.1104	0.0253	0.0671	0.1656
27	17	4	0	0.0844	0.0224	0.0473	0.1349
28	13	7	0	0.0390	0.0156	0.0160	0.0782
29	6	3	1	0.0195	0.0111	0.0053	0.0517
30	2	1	1	0.0097	0.0089	0.0011	0.0428

Continued on the next page ...

Table 4: Panel 2 Survival function for females:

Time	Beg. Total	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf. Int.]	
1	186	5	0	0.9731	0.0119	0.9366	0.9887
2	181	2	0	0.9624	0.0140	0.9227	0.9819
4	179	6	0	0.9301	0.0187	0.8827	0.9588
5	173	5	0	0.9032	0.0217	0.8508	0.9379
6	168	42	0	0.6774	0.0343	0.6051	0.7394
7	126	8	0	0.6344	0.0353	0.5608	0.6990
8	118	8	0	0.5914	0.0360	0.5172	0.6581
9	110	5	0	0.5645	0.0364	0.4902	0.6322
10	105	9	0	0.5161	0.0366	0.4421	0.5851
11	96	7	0	0.4785	0.0366	0.4051	0.5481
12	89	10	0	0.4247	0.0362	0.3531	0.4944
13	79	4	0	0.4032	0.0360	0.3325	0.4727
14	75	5	0	0.3763	0.0355	0.3070	0.4454
15	70	12	0	0.3118	0.0340	0.2467	0.3790
16	58	5	0	0.2849	0.0331	0.2220	0.3509
17	53	2	0	0.2742	0.0327	0.2122	0.3396
18	51	9	0	0.2258	0.0307	0.1687	0.2881
19	42	4	0	0.2043	0.0296	0.1498	0.2649
20	38	4	0	0.1828	0.0283	0.1311	0.2414
21	34	3	0	0.1667	0.0273	0.1172	0.2237
22	31	4	0	0.1452	0.0258	0.0990	0.1997
23	27	3	0	0.1290	0.0246	0.0857	0.1815
24	24	2	0	0.1183	0.0237	0.0769	0.1693
25	22	6	0	0.0860	0.0206	0.0513	0.1318
26	16	2	1	0.0753	0.0193	0.0432	0.1190
27	13	2	0	0.0637	0.0180	0.0345	0.1052
28	11	5	0	0.0347	0.0137	0.0146	0.0693
29	6	3	3	0.0174	0.0099	0.0048	0.0460

The conditional probability of failure when plotted against the continuous time of the study is called the hazard rate. As has been shown in equations 20 through 22, the hazard rate comprises the basis for the dependent variable in the proportional hazards regression analysis that we will undertake after our summary description of the data in terms of the fundamental rates. For this reason, many researchers would like to see the hazard rate data and the graphs that describe it. The hazard rate data are listed in panels one and two of Table 5, and they are graphed in Figures 5 and 8.

Table 5: Panel 1: The Hazard function for the males

Time	Beg. Total	Fail	Net Lost	Failure Function	Std. Error	[95% Conf. Int.]	
1. male							
1	154	2	0	0.0130	0.0091	0.0033	0.0509
2	152	4	0	0.0390	0.0156	0.0177	0.0847
3	148	3	0	0.0584	0.0189	0.0308	0.1093
4	145	1	0	0.0649	0.0199	0.0355	0.1173
5	144	5	0	0.0974	0.0239	0.0599	0.1564
6	139	39	0	0.3506	0.0385	0.2811	0.4316
7	100	8	0	0.4026	0.0395	0.3300	0.4845
8	92	7	0	0.4481	0.0401	0.3736	0.5300
9	85	8	0	0.5000	0.0403	0.4242	0.5813
10	77	8	0	0.5519	0.0401	0.4755	0.6317
11	69	1	0	0.5584	0.0400	0.4820	0.6379
12	68	2	0	0.5714	0.0399	0.4950	0.6503
13	66	6	0	0.6104	0.0393	0.5343	0.6873
14	60	2	0	0.6234	0.0390	0.5475	0.6995
15	58	1	0	0.6299	0.0389	0.5542	0.7056
16	57	5	0	0.6623	0.0381	0.5875	0.7358
17	52	5	0	0.6948	0.0371	0.6213	0.7656
18	47	7	0	0.7403	0.0353	0.6692	0.8066
19	40	4	0	0.7662	0.0341	0.6970	0.8296
20	36	5	0	0.7987	0.0323	0.7321	0.8578
21	31	4	0	0.8247	0.0306	0.7607	0.8799
23	27	3	0	0.8442	0.0292	0.7825	0.8962
24	24	2	0	0.8571	0.0282	0.7971	0.9069
26	22	5	0	0.8896	0.0253	0.8344	0.9329
27	17	4	0	0.9156	0.0224	0.8651	0.9527
28	13	7	0	0.9610	0.0156	0.9218	0.9840
29	6	3	1	0.9805	0.0111	0.9483	0.9947
30	2	1	1	0.9903	0.0089	0.9572	0.9989

Continued on the next page ....

Table 5: Panel 2: The Hazard function for the females

	Beg.		Net	Failure	Std.		
Time	Total	Fail	Lost	Function	Error	[95% Conf.	Int.]
2. female							
1	186	5	0	0.0269	0.0119	0.0113	0.0634
2	181	2	0	0.0376	0.0140	0.0181	0.0773
4	179	6	0	0.0699	0.0187	0.0412	0.1173
5	173	5	0	0.0968	0.0217	0.0621	0.1492
6	168	42	0	0.3226	0.0343	0.2606	0.3949
7	126	8	0	0.3656	0.0353	0.3010	0.4392
8	118	8	0	0.4086	0.0360	0.3419	0.4828
9	110	5	0	0.4355	0.0364	0.3678	0.5098
10	105	9	0	0.4839	0.0366	0.4149	0.5579
11	96	7	0	0.5215	0.0366	0.4519	0.5949
12	89	10	0	0.5753	0.0362	0.5056	0.6469
13	79	4	0	0.5968	0.0360	0.5273	0.6675
14	75	5	0	0.6237	0.0355	0.5546	0.6930
15	70	12	0	0.6882	0.0340	0.6210	0.7533
16	58	5	0	0.7151	0.0331	0.6491	0.7780
17	53	2	0	0.7258	0.0327	0.6604	0.7878
18	51	9	0	0.7742	0.0307	0.7119	0.8313
19	42	4	0	0.7957	0.0296	0.7351	0.8502
20	38	4	0	0.8172	0.0283	0.7586	0.8689
21	34	3	0	0.8333	0.0273	0.7763	0.8828
22	31	4	0	0.8548	0.0258	0.8003	0.9010
23	27	3	0	0.8710	0.0246	0.8185	0.9143
24	24	2	0	0.8817	0.0237	0.8307	0.9231
25	22	6	0	0.9140	0.0206	0.8682	0.9487
26	16	2	1	0.9247	0.0193	0.8810	0.9568
27	13	2	0	0.9363	0.0180	0.8948	0.9655
28	11	5	0	0.9653	0.0137	0.9307	0.9854
29	6	3	3	0.9826	0.0099	0.9540	0.9952

**Table 6 Panel 1: Cumulative Hazard rates of time to Level 25 Depression**

Time	Beg. Total	Fail	Net Lost	Nelson-Aalen Cum. Haz.	Std. Error	[95% Conf. Int.]	
1. male							
1	154	2	0	0.0130	0.0092	0.0032	0.0519
2	152	4	0	0.0393	0.0160	0.0177	0.0875
3	148	3	0	0.0596	0.0199	0.0310	0.1145
4	145	1	0	0.0665	0.0210	0.0358	0.1236
5	144	5	0	0.1012	0.0261	0.0610	0.1679
6	139	39	0	0.3818	0.0520	0.2924	0.4985
7	100	8	0	0.4618	0.0592	0.3592	0.5936
8	92	7	0	0.5379	0.0658	0.4232	0.6836
9	85	8	0	0.6320	0.0737	0.5028	0.7943
10	77	8	0	0.7359	0.0824	0.5909	0.9164
11	69	1	0	0.7504	0.0836	0.6031	0.9336
12	68	2	0	0.7798	0.0862	0.6279	0.9684
13	66	6	0	0.8707	0.0938	0.7049	1.0755
14	60	2	0	0.9040	0.0968	0.7330	1.1150
15	58	1	0	0.9213	0.0983	0.7474	1.1355
16	57	5	0	1.0090	0.1058	0.8215	1.2392
17	52	5	0	1.1051	0.1142	0.9025	1.3533
18	47	7	0	1.2541	0.1273	1.0278	1.5302
19	40	4	0	1.3541	0.1368	1.1108	1.6506
20	36	5	0	1.4930	0.1502	1.2257	1.8185
21	31	4	0	1.6220	0.1635	1.3312	1.9763
23	27	3	0	1.7331	0.1756	1.4209	2.1139
24	24	2	0	1.8164	0.1853	1.4873	2.2184
26	22	5	0	2.0437	0.2113	1.6688	2.5028
27	17	4	0	2.2790	0.2419	1.8510	2.8059
28	13	7	0	2.8175	0.3161	2.2613	3.5104
29	6	3	1	3.3175	0.4281	2.5761	4.2721
30	2	1	1	3.8175	0.6582	2.7228	5.3523

Continued on next page ...

Table 6 Panel 2 Cumulative hazard rate for level 25 depression in women

Time	Beg. Total	Fail	Net Lost	Nelson-Aalen Cum. Haz.	Std. Error	[95% Conf. Int.]	
2. female							
1	186	5	0	0.0269	0.0120	0.0112	0.0646
2	181	2	0	0.0379	0.0143	0.0181	0.0796
4	179	6	0	0.0715	0.0198	0.0415	0.1231
5	173	5	0	0.1004	0.0237	0.0632	0.1593
6	168	42	0	0.3504	0.0453	0.2720	0.4513
7	126	8	0	0.4138	0.0505	0.3258	0.5257
8	118	8	0	0.4816	0.0559	0.3836	0.6047
9	110	5	0	0.5271	0.0595	0.4225	0.6576
10	105	9	0	0.6128	0.0660	0.4962	0.7568
11	96	7	0	0.6857	0.0715	0.5589	0.8413
12	89	10	0	0.7981	0.0799	0.6560	0.9710
13	79	4	0	0.8487	0.0838	0.6994	1.0299
14	75	5	0	0.9154	0.0889	0.7567	1.1074
15	70	12	0	1.0868	0.1018	0.9046	1.3058
16	58	5	0	1.1730	0.1088	0.9780	1.4069
17	53	2	0	1.2108	0.1120	1.0099	1.4515
18	51	9	0	1.3872	0.1266	1.1601	1.6588
19	42	4	0	1.4825	0.1352	1.2398	1.7726
20	38	4	0	1.5877	0.1451	1.3274	1.8992
21	34	3	0	1.6760	0.1538	1.4001	2.0062
22	31	4	0	1.8050	0.1668	1.5060	2.1633
23	27	3	0	1.9161	0.1787	1.5960	2.3004
24	24	2	0	1.9994	0.1881	1.6627	2.4044
25	22	6	0	2.2722	0.2186	1.8817	2.7437
26	16	2	1	2.3972	0.2358	1.9768	2.9069
27	13	2	0	2.5510	0.2597	2.0896	3.1143
28	11	5	0	3.0056	0.3298	2.4240	3.7267
29	6	3	3	3.5056	0.4383	2.7437	4.4790

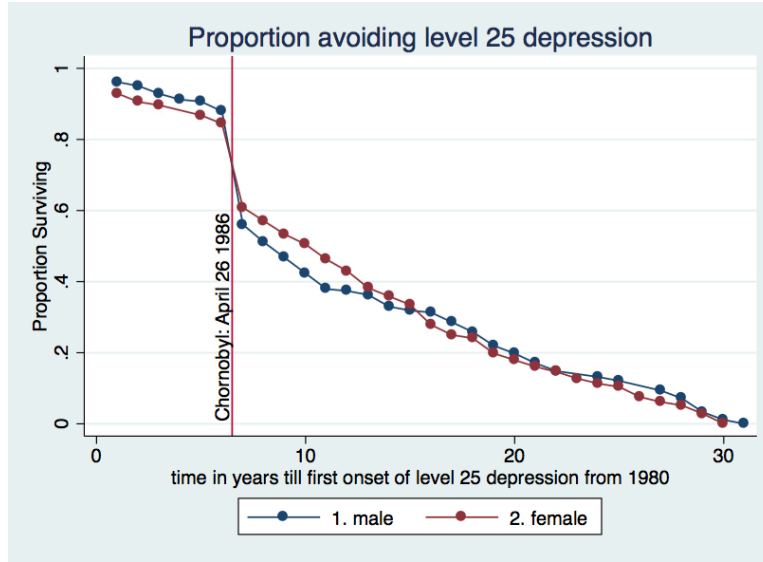


Figure 3: Survival probability by gender

In Figure 3, we see that the male and the female groups were very similar to one another insofar as they both suffered a decline in probability of surviving, by which we mean not experiencing, depression after Chernobyl. At first, the males seem to have become more depressed at level 25. However, after 1994 the amount of level 25 depression seems to have become about the same for both males and females.

Figure 4 illustrates the proportion succumbing to level 25 depression by gender. This is the conditional probability of level 25 depression broken down by gender. We can see that the rates are very similar and quite possibly not statistically different from one another. The hazard rate suddenly rises at the time of Chernobyl, six years after the beginning of the study time being recalled. This abrupt rise is consistent with the sudden drop of survival probability in the previous figure and we will have to explore in greater detail the reasons for these abrupt changes. If we can assume that all other things remained essentially the same, there is *prima facie* evidence that the general level 25 depression was associated with the onset of the Chernobyl accident.

Although the graphs allow us to identify immediately salient changes in the pattern, we sometimes need the tables to identify less pronounced changes in the survival or hazard rates. We observe pronounced depression (failure) rates in the hazard, and cumulative hazard at 12 and 15 years after the study began, particularly among women in panel two of Tables 5 and 6. These pronounced failure rates take place in 1992 and 1995.

To place these events in historical perspective, we endeavor to discuss a brief timeline of prominent events in Ukrainian and Russian history in and around

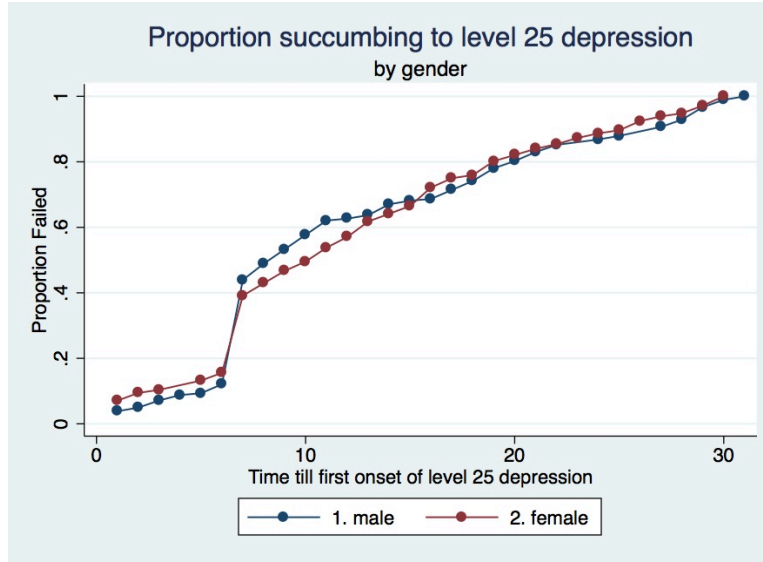


Figure 4: Hazard rate by gender

1992 and 1995. We recall that the Soviet Union collapsed in December of 1991, and the Ukraine was among the countries to declare independence and to form the Commonwealth of Independence States, made up of former nations of Soviet Russia. Ukrainians voted overwhelmingly for independence from Russia. Leonid Kuchma succeeded Leonid Kravchuk as president [1]. In December of 1991 Leonid Kravchuk, former chairman of the Rada, was elected president as a new government was formed in the Ukraine.

In 1992, The Ukraine rejected a proposal of Boris Yeltsin for a military force consisting of unified Ukrainian, Moldovian, and Azherbaijanian troops. In 1994, there may have been much discussion of the proposals for a new constitution during 1995 and early 1996. In March of 1995 Vitaly Massol, the Ukrainian premier, resigned. By June of 1996, a new constitution was adopted in the Ukraine[20], [21].

Amidst this political change most people were elated while a minority would be very dejected. The increase in depression recorded on the part of some of the respondents at that time is not surprising, and would be expected. The Ukraine in 1991 dropped price controls and Boris Yeltsin deregulated them in January 1992 to stimulate production. In 1992 Sevastopol, which used to be a closed Soviet port on the Black sea finally was opened to the ships from the outside world. Meanwhile, the rise in prices no doubt worried many pensioners living by modest means.

In January 1995, Russian forces suppressed a bloody rebellion in Chechnya. In February, Boris Yeltsin fired three of his top assistants for losses to the Russian troops and massive human rights abuses in Chechnya. By June, Chechnyan



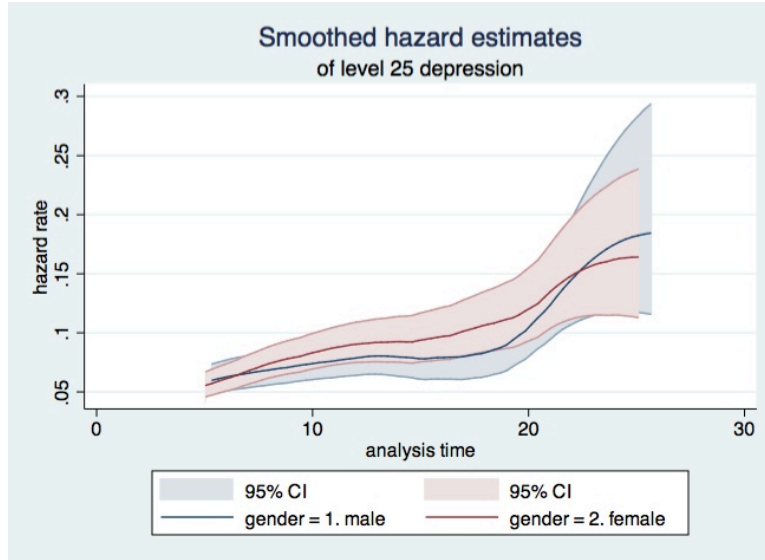


Figure 5: Smoothed hazard functions by gender

rebels seized a hospital where they held 1500 administrators, doctors, staff and patients hostage. Russian troops stormed the hospital and freed the hostages, but over 150 of the people died in the process. By December heavy fighting broke out in Chechnya again when rebels disrupted elections[16].

When the smoothed hazard rates are broken down by gender, as shown in Figure 5, smoothing attenuates abrupt changes. In this figure, we see nothing before Chernobyl and the lines appear for the first time at about the time of the disaster. Although there is some difference due to gender, the overlapping confidence intervals reveal that the hazard rates of the two genders are not significantly different from one another in general. However, if we examine this graph more closely it appears that the sharp rise in this hazard rate takes place around the 19th year mark. We will explore the events around this time in a moment.

In Figure 6, the hazard rates for trichotomized age groups are illustrated. The upper third (group 3) is the older of the three groups, and, not surprisingly, it appears to suffer more than the other groups at the beginning and end of the study. This older group is the least stable of the three groups. The middle third of the age groups to have the middle level of stability—revealing higher hazard in the middle of the study. Finally, the younger third appears to be the most stable of all the groups with a more or less constant increase in the hazard rate over the study time.

When the confidence intervals are included in Figure 7, the overlap among the age groupings appears to become more distinct as the study time passes. At first, there does not seem to be a significant difference among the age groups,

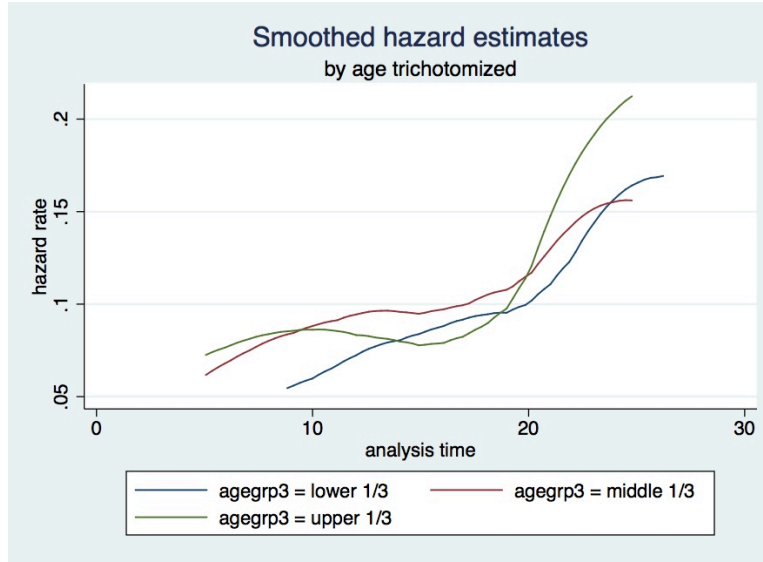


Figure 6: Hazard rate by age group

whereas later on distinctions do become apparent. As time passes, the older third of the respondents exhibits a higher hazard rate than the others.

Researchers engaging in longitudinal studies of psychological traits and disorders must focus on cumulative effects. Therefore, we examine the cumulative hazard rate as measured by the Nelson-Aalen cumulative hazard formula. We examine the cumulative hazard rates of the two genders and the three age groups. The Nelson-Aalen cumulative hazard rates are given in Figure 8. The steady climb in the cumulative hazard rate indicates that over time the likelihood of the men and women succumbing to depression is increasing. We will explore the reasons for this in our endeavor to build semi-parametric and parametric models.

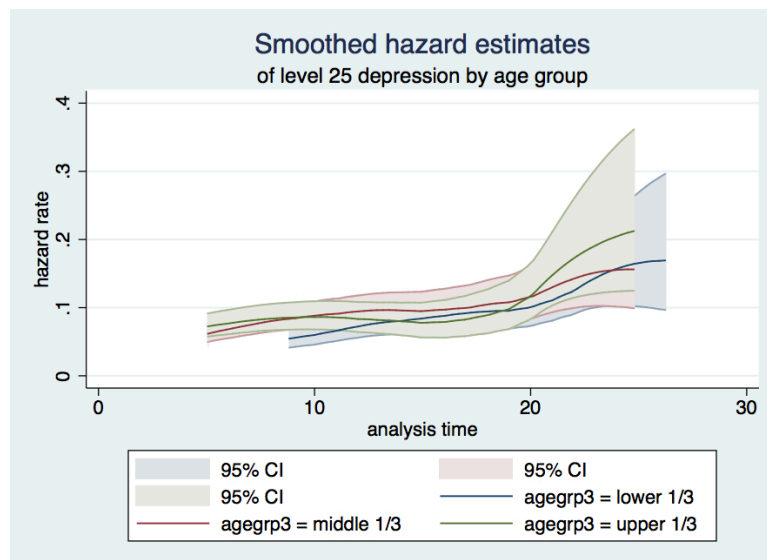


Figure 7: Hazard rate by age group with their confidence limits

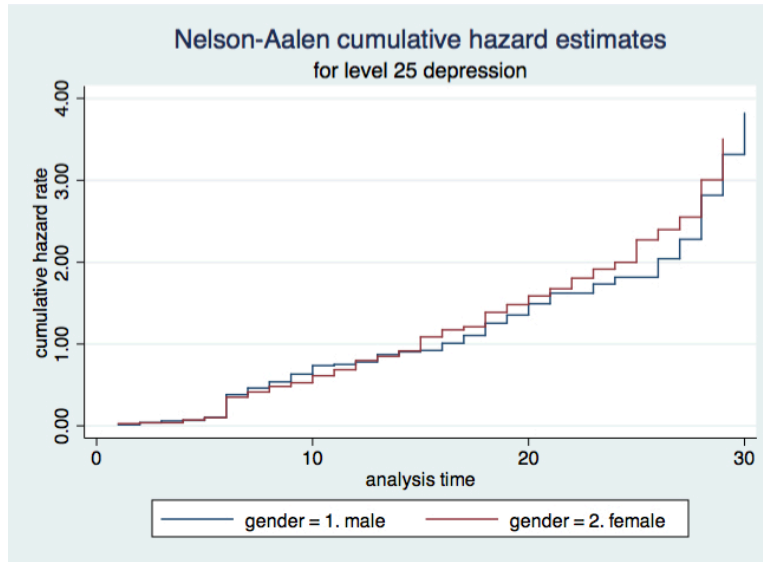


Figure 8: Cumulative hazard rates by gender

We can summarize level 25 depression by breaking down the sample by median failure rate and by incidence rate. We break down the median first by gender and then by age group in the following three tables.

Table 7 Median failure by gender

gender	no. of subjects	50%	Std. Err.	[95% Conf. Interval]	
1. male	154	9	.7756046	8	13
2. female	186	11	.78609	9	12
total	340	10	.7372445	9	12

Trichotomizing age, we obtain the following groups.

Table 8 Median failure by age group

agegrp3	no. of subjects	50%	Std. Err.	[95% Conf. Interval]	
lower 1/3	96	15	1.223681	12	17
middle 1/3	130	10	.8135431	9	12
upper 1/3	114	7	.3479512	6	9
total	340	10	.7372445	9	12

However, epidemiologists prefer to think of these phenomena in terms of the

incidence rates, which in continuous time are prevalence rates:

Table 9 Incidence rate by gender

gender==males						
	time at risk	incidence rate	no. of subjects	Survival time		
				25%	50%	75%
total	1980	.0767677	154	6	9	19
gender==females						
	time at risk	incidence rate	no. of subjects	Survival time		
				25%	50%	75%
total	2360	.0771186	186	6	11	18

At each interval the one proportion of the respondents has not lapsed into a depressive state whereas another proportion has indeed lapsed into a depressive state. Because we do not loose any of the respondents to follow-up, we do not consider them censored. However, those who lapse into depression can be deemed censored at that point because for all intents and purposes of the analysis, the study time terminates at that point. Those who remain depressed at that point are deemed right-censored, so half of them are subtracted from the risk set before the conditional probability of depression is computed. For the multiple episode models we consider later, this becomes slightly more complicated.

## 4.2 Survival analysis

The first model we examine with your sampling weights is the Cox regression model. The dependent variable is the hazard rate. We enter variables in blocks to see which are statistically significant.

With a proportional hazards regression, we are using the log relative hazard as the basis for our dependent variable. We need not worry about the baseline hazard in these models, for it matters little with respect to the impact that the parameters have the on the log relative hazard, if we assume proportionality of the hazards..

### 4.2.1 Model building strategy

The employment of sampling weights for model building generated huge models of hundreds of variables, all of which were reportedly statistically significant at the 0.000 level. This fact made model fitting difficult as long as population totals were used. Models could contain literally hundreds of variables, all of which appear to be statistically significant. This did not seem to be an efficient method of extracting order from chaos.

Because our sample was based on a random generation of telephone numbers, our design-based models, which do not apply the sampling weights, are fundamentally representative. To better enable us to assess the relative statis-

tical significance of individual variables, we build our preliminary models with a design-based approach.

We want to reduce the noise level in the model so that make efficient use out of the signal to noise ratio that the design-based models afford. To test theory, we test sets of theoretical variables for significant risk factors or variables. After we discover which variables in a theoretical class of variables are statistically significant, we can test these candidate variables in a final omnibus model to see which are retained when all are put together. Because the accumulation of variable sets generates unanticipated collinearities which cause some of the chosen variables to be automatically dropped from the modeling process, the construction of a full model, as advocated by Frank Harrell, Jr. may require data reduction and some trimming [7, 58-85]. Approximations of a full model may be necessitated, for example, when some of the dummy variables required representation of categorical variables are automatically deleted from the model to avert a multicollinearity trap.

For the purpose of comprehending the relative impacts of effects of a nuclear accident or incident, we enter the variables in separate meaningful classes. Because the nesting has been destroyed by the customary culling of collinear covariates, the  $R^2$  change measure will be deprived of the meaning it would have in a single level hierarchical regression analysis. Nonetheless, for each set of categories being tested, we can examine the pseudo- $R^2$  to assess the relative importance of the set of variables in explaining the relative log hazard of level 25 depression.

Although the specific-to-general approach is helpful for hypothesis testing, it is not optimal for final model-building. We therefore retest our models proceeding in the other direction—from general-to-specific in accordance with the Hendry and Richard (1982) recommendations[8, 3-33]. This permits us to test all of the selected variables with simultaneous tests possessing the same statistical power to determine which variables should be retained for the model to endow it with optimal omnibus goodness of fit. The Hendry et al. approach has been found to yield optimal models.

The variables were entered in blocks so we could analyze the proportional reduction of error due to different sets of variables. We could thereby obtain a sense of the importance not only of individual parameters, but also of sets of them. It is hoped that the proportional reduction of error due to the sets of variables would provide information about the relative importance of the class of risk factors, stressors, or buffers under consideration in that block. There were approximately 10 blocks of variables entered.

The first block entered is the geo-socio-demographic block consisting of the raions in which people reside along with salient sociodemographic characteristics. Age, educational attainment, marital status, number of children, occupation, and income sufficiency were among the variables included in this block.

The next block added were those consisting of major negative life events—including deaths, divorces, separations, catastrophes, and accidents. Distance from Chernobyl and reconstructed minimum and maximum average dosages per person of *Cesium*<sup>137</sup>, in  $\mu$ Grays, were included in this block. By classifying

these effects as a group, we should be able to ascertain the aggregated impact is on the probability of a person experiencing level 25 depression.

The third set of variables that we add to the model are psychological stresses and hassles. These include family related, job-related, housing related, financial, housing, and health related hassles. By entering these risk factors as a separate group, we hope to be able to distinguish their impact from those mentioned above.

The fourth class of variables added to the model are the buffers and supports, which could synergistically counter the stresses and strains sustained by the respondent. These supports consists of family, partner, or Chornobyl support provided by the government.

The fifth category of effects we test are those related to self-perceived physical and mental illnesses. They involve self-assessment of physical and mental health. They entail the mention of specified ailments. They entail hospital and doctor visits for such complaints.

The sixth category pertains the medically diagnosed illnesses coded according to the International classification of diseases in version nine.

The seventh category pertains to health behaviors. These include such things as smoking, drinking vodka, hard liquor, or beer, and taking pain pills.

The eighth category are the scores of the respondents on the health scales – the Nottingham health profile, the basic symptom inventory, the coping scales, as well as the Mississippi PTSD scale.

In the ninth category, we have three forms of hazards awareness. First, there are those factors related to general environmental hazards awareness. This includes items environmental and nutritional issues, political and economic effects on the environment, how much of the environment is polluted.

Second, questions relating to general radiation knowledge and awareness are included. For example, these included items about the health effects of radiation, the effects of radiation on pregnancy, and whether some radiation is safe.

Thirdly, Chornobyl related questions are asked. The location of the respondent at the time of the accident, how far away he or she lived and worked, whether most of the cancer cases in the Oblasts under consideration stem from Chornobyl, and the extent of the pollution due to Chornobyl, as well as whether the respondent's or his or her family's health was affected by Chornobyl. Whether he or she was relocated or injured as a result of Chornobyl was also asked.

The final model reveals the extent to which these factors impacted the conditional probability of depression on the part of the respondents. However, we present two versions of the models. The first model is a full model with all parameters in the model. We present this model to represent all of dummy variables representing categorical variables.

Stata will drop those parameters if they are collinear with other included parameters. Sometimes the collinear parameters are the dummies needed to completely estimate a categorical variable. If a large proportion of parameter estimates in a full model happen to be statistically nonsignificant, the likelihood

surface over which the estimation algorithm searches for a hill to climb may become too flat for consistent elevation of altitude in the hill- climbing process. Under these circumstances, items that are highly nonsignificant are dropped from the full model. The objective is to provide a likelihood surface that can challenge the mountaineer. So the retention of too many nonsignificant terms may deprive the model of the power to detect smaller effect sizes that really exist. In hopes of properly estimating the categories of factor variables, we do endeavor to estimate a full model if that is possible. Because of the draining of power from such a model, we also estimate a trimmed model.

In the trimmed model, all collinear parameter estimates are dropped. So are the nonsignificant parameter estimates. Because multicollinearity causes elasticity of the p values, we use a cut-off of .10 rather than 0.05, for dropping nonsignificant variables. However, only those less than 0.05 are deemed statistically significant. If a categorical variable is represented by a series of dummy variables, one of which is statistically significant, we try to retain all that Stata will permit us to retain for proper evaluation of the categorical factor. It is not always possible to do so if one of the dummy variables indicating one of the categories is collinear with the other items and the inclusion of it precludes convergence of the estimation algorithm. We drop those items as well. To preserve the power of the model, all other non-statistically significant variables are pruned from the model.

### **4.3 Geo-Socio-Demographic Factors**

#### **4.3.1 Male risk factors**

We examine those factors which appear to influence the time to onset of the first spell of depression for all respondents. We begin our model building with a single transitional analysis. What factors explain the onset of the first spell of depression? We examine a set of classes of events that may explain this phenomena, which we have just discussed above. For each of these categories, we test a set of variables considered part of that set, for each gender. The first category consists of geographic, demographic, and sociological factors that retain significance after trimming out the noise from the non-significant effects. A full set of variables often consists of 30 to 50 variables. After trimming the statistically nonsignificant variables from the set, we are left with a smaller selection of those whose significance level is at least 0.100 or less. In Table 10, we are presented with relative hazard ratios and their standard errors, their z scores and the probability of obtaining such a z score by chance. How do we interpret the relative hazard ratios?



We can interpret the relative hazard ratios as a percentage probability of experiencing depression, per unit change in the explanatory variable. In Table 10 we have a list of variables significant at the 0.10 level. The variables indicate the area of the telephone area code of the respondent– whether living in Kiev, Malinskiy, or Zhitomirskiy raions. The next variable is the time-varying age of the respondent and the one following that is whether the respondent is employed part-time. The next four variables describe a rising comfort level within wave two of our study due to the level of income. Inc1w2 indicates a condition of not being able to afford the basic necessities of life, whereas inc2w2 is barely able to afford the necessities of life, to being able to afford necessities to a few luxuries to the level 4, which accounts for comfortable living, saving, and being able to afford luxuries. Let us first consider hazard ratios greater than one. Residents with telephone area codes within the Malinskiy raion are 2,776 % more likely to be depressed as those outside the area of the three listed areas  $(28.76-1.00)*100$ . The area codes not specified in the list comprise the reference category or region. We can also consider age as a time-varying covariate. It changes with the reference year. The reference point for this category may be the age of the respondent at any year within the recollected span of time .That age of the respondent results in a 2.25 % – that is, a  $(1.0225 - 1)*100$  percent – change on the probability of becoming depressed.

Table 10. Male hazard ratios of geo-socio-demographic variables						
No. of subjects =	154			Number of obs =	154	
No. of failures =	152					
Time at risk =	1980					
				LR chi2(9) =	28.65	
Log likelihood =	-622.33694			Prob > chi2 =	0.0007	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Kyivskiy	1.450532	.3011604	1.79	0.073	.9656063	2.178985
Malinskiy	28.76348	32.21669	3.00	0.003	3.202203	258.3653
Zhitomirskiy	1.841395	.6101294	1.84	0.065	.9618535	3.525208
tvage	1.022487	.0079534	2.86	0.004	1.007016	1.038194
emplw13	1.747173	.5432576	1.79	0.073	.9498774	3.213694
inc1w2	.2410974	.1021518	-3.36	0.001	.1050854	.5531497
inc2w2	.2922535	.1068632	-3.36	0.001	.1427302	.5984167
inc3w2	.337205	.1308009	-2.80	0.005	.1576578	.7212281
inc4w2	.1127031	.0640196	-3.84	0.000	.0370187	.3431232
Test of proportional-hazards assumption						
Time: Time						
			chi2	df	Prob>chi2	
global test			4.86	9	0.8461	

We can consider a hazard ratio less than unity– such as that of the insufficiency of the salary to purchase the basic necessities in the decade from 1987 through 1996 - represented by the variable named inclw2. The effect

this variable has on the percentage probability of experiencing depression is approximately -75.9%. We compute this percentage by taking the parameter, subtracting from it a one, and multiplying by 100:  $(0.241-1) * 100$  which is about 76% chance of a respondent in this condition experiencing depression. Even more interesting is the improbability of -88% –computed by  $[(0.1127 - 1)*100]$  that a person, indicated by variable, `inc1w4`, living comfortably with the ability to afford luxuries would experience depression. Similarly, the probability of a person experiencing depression who can barely afford the necessities of life during wave two (1987 through 1996) represented by variable, `inc2w2`, is -70.8 %  $(.292 - 1)*100$ . In this way, we can compute the percentage change on the probability of experiencing depression indicated by each of the explanatory variables.

Whenever such an analysis is performed, it is presumed to extend over the full span of the study time. In other words, it is presumed that the parameter estimates are constant over time and do not interact with it. This assumption is called the proportional hazards assumption. If there were an interaction with time, the hazards would not be constant over time. However, to be sure that we can count on these parameter estimates, we need to test whether that interaction is non-significant. The results of this test are contained at the bottom of Table 10, where a statistically nonsignificant result provides evidence that the fundamental assumption of a proportional hazards regression is fulfilled. However, for the males geo-sociodemographic variables yielded an  $R_D^2$ , accounting for only 3.449% of the total proportional reduction of error in the male model. We offer a definition and detailed explanation of the  $R_D^2$  in section 4.13.

Because these are nonlinear equations, it is helpful to illustrate the different effects on the cumulative baseline hazards. We display the cumulative baseline hazard functions for men residing in these areas in Figure nine and for women in Figure ten.

#### 4.3.2 Female risk factors

Table 11 displays the geo-socio-demographic risk factors for the women, which appear to be different from those for the men. But the legend describing those variables appears on the following page. In this case, age is not time-varying, but rather the age at the time of the interview. The effect on experiencing depression is only a little more than one percent. Apart from the area of residence of the respondent, the age at the time of the interview has barely two percent impact on the probability of experiencing depression.

What is interesting is that the occupation of the respondent is more likely to be positively associated with the probability of experiencing depression in 1986 than it is in the years since 1997 up to now (wave three). Whereas the hazard ratios appear to be positive for the occupation of the female respondent in wave one, they seem to be negatively associated with the likelihood of experiencing depression in later years. For 1986, which is wave one, all of these occupational role appear to be positive or greater than one. However, in the years during wave two or even those years since 1997 or at the time of the interview, which

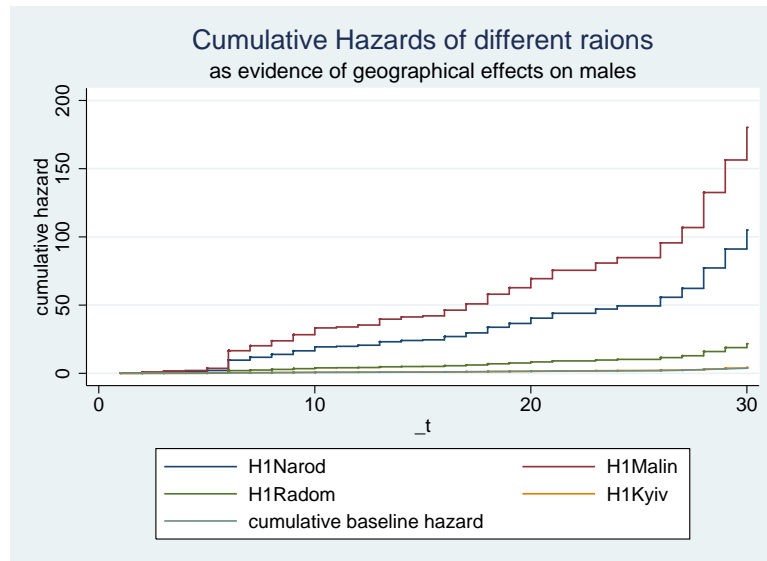


Figure 9: Male baseline cumulative hazard functions

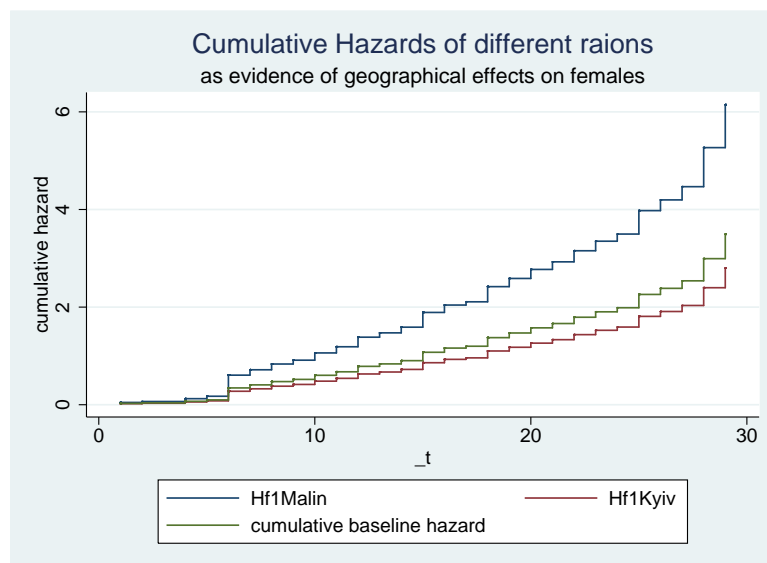


Figure 10: Female baseline cumulative hazard functions

extended from 2009 through 2011, the occupational role appears to be negative or less than unity. More likely than not, this shift in sign of the hazard ratios could indicate a period effect of the occupation of the female respondent.

In the 1970s and 1980s there was a feminist movement in the United States that staunchly advocated equal rights for women in many respects. It is possible that the Perestroika and Glasnost undertaken by Gorbachev, combined with some cultural spillover from the United States, had a reformist effect on the role of women in Ukrainian sector of the the former Soviet Union as well. Whatever change took place, the occupational role of women had become, across the whole labor force, negatively associated with the onset of depression after Chornobyl.

Table 11 variable dictionary

variable name	storage type	display format	value label	variable label
Irpenskiy	byte	%8.0g		ranown==67
Zhitomirskiy	byte	%8.0g		ranown==102
age	byte	%8.0g		* Respondent's age
occ1w1	byte	%15.0g	LABJ	profess executive administration in 1986
occ2w1	byte	%15.0g	LABJ	technical sales admin support in 1986
occ3w1	byte	%15.0g	LABJ	service occup protective services in 1986
occ4w1	byte	%15.0g	LABJ	precision prod mechan craft construction in 1986
occ5w1	byte	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
occ6w1	byte	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1986
occ7w1	byte	%15.0g	LABJ	homemaking or caregiving in 1986
occ8w1	byte	%15.0g	LABJ	student in 1986
occ2w2	byte	%15.0g	LABJ	technical sales admin support in 1996
occ3w2	byte	%15.0g	LABJ	service occup protective services in 1996
occ4w2	byte	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	byte	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
occ6w2	byte	%15.0g	LABJ	farming agricul forestry fishing trapping logging in 1996
occ7w2	byte	%15.0g	LABJ	homemaking caregiving in 1996
occ8w2	byte	%15.0g	LABJ	student in 1996
occ1w3	byte	%15.0g	LABJ	professional executive administration now
occ2w3	byte	%15.0g	LABJ	technical sales admin support now
occ3w3	byte	%15.0g	LABJ	service occup protective services now
occ5w3	byte	%15.0g	LABJ	factory laborer machinist transp cleaner now
occ6w3	byte	%15.0g	LABJ	farming agricul forestry fishing trapping logging now
occ7w3	byte	%15.0g	LABJ	homemaking or caregiving now

Table 11 Female geo-socio-demographic risk factors

Cox regression -- Breslow method for ties

No. of subjects =	186	Number of obs =	186
No. of failures =	182		
Time at risk =	2360		
Log likelihood =	-776.39392	LR chi2(18) =	43.26
		Prob > chi2 =	0.0007

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Irpenskiy	.3808437	.2075558	-1.77	0.077	.1308733	1.108262
Zhitomirskiy	2.005653	.5729949	2.44	0.015	1.145714	3.511038
age	1.01596	.009671	1.66	0.096	.9971805	1.035092
occ1w1	189.8265	231.3212	4.31	0.000	17.42164	2068.354
occ2w1	476.479	628.6976	4.67	0.000	35.88497	6326.665
occ3w1	169.0634	209.6638	4.14	0.000	14.87416	1921.616
occ4w1	47.25783	53.49484	3.41	0.001	5.139635	434.5256
occ5w1	198.6872	254.2804	4.13	0.000	16.17334	2440.843
occ6w1	263.9112	346.1259	4.25	0.000	20.1877	3450.078
occ7w1	121.8906	152.4571	3.84	0.000	10.50299	1414.579
occ8w1	151.1698	185.894	4.08	0.000	13.575	1683.412
occ2w2	.2729525	.1585684	-2.24	0.025	.0874162	.8522797
occ1w3	.0054704	.0066099	-4.31	0.000	.0005123	.0584148
occ2w3	.0062961	.0078852	-4.05	0.000	.0005408	.0733003
occ3w3	.0053138	.0064823	-4.29	0.000	.0004864	.0580478
occ5w3	.0070036	.0091984	-3.78	0.000	.0005338	.0918906
occ6w3	.0072184	.0096262	-3.70	0.000	.0005288	.0985313
occ7w3	.0071062	.0084545	-4.16	0.000	.0006902	.0731703

For the females, these factors provided an  $R^2_D$  of 0.1534, which accounted for approximately 17.259% reduction in the total proportional error. The Breslow approximation for tied ranks adjust the first failure for the previous failures but not the others. It is an approximation of the marginal probability is not computer intensive.

#### 4.4 Major negative life events

If anything would have a major effect on the psychological and/or physical wellbeing of a respondent, we might think that major negative life events—such as a trauma or personal or professional crisis— would be the kind of factors that would have such an impact. It is to this category of events that we turn our attention next. Crises usually involve extreme threat, sudden appearance, and a short time frame for effective response. But preparation for emergency response in terms of prepositioning critical resources, training the coordinators for dealing with contingencies of effective response may mitigate if not eliminate the threat altogether. If crisis management and communication are properly handled, damage and emerging needs are assessed, monitored, and coordinated so that a minimum amount of damage and pain takes place.

We may be able to appreciate what did not work properly if we are able to determine the extent to which major negative life events were incorporated into this tragedy to impact early onset of depression.

Among the males in the study, accidents, catastrophes, and deaths were risk factors during 1986 that seem to have impact on the conditional probability of onset of depression, revealed in Table 12. When these variables are taken together, they get a  $R2_D = 0.1088$  for the males, accounting for 12.654% of the total proportional variance explained.

As for the percentage impact on the dependent variable of the explanatory variables, we see from this table that accidents accounted for 377% increase in the hazard of depression, whereas catastrophes accounted for 179% of them, and deaths had only approximately a 156% impact on the time till onset of depression.

Table 12 Male negative life events

```
Cox regression -- Breslow method for ties
No. of subjects =          154          Number of obs   =          154
No. of failures =           152
Time at risk    =          1980
Log likelihood   =   -626.60657
LR chi2(3)       =          20.11
Prob > chi2      =          0.0002
```

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
accdw1	3.775052	1.655247	3.03	0.002	1.59844	8.915575
cataw1	1.786592	.339442	3.05	0.002	1.231125	2.592679
deaw2	1.558699	.211399	3.27	0.001	1.194862	2.033325

Test of proportional-hazards assumption

Time: Time

	chi2	df	Prob>chi2
global test	1.73	3	0.6295

Legend for table 13

variable name	storage type	display format	value label	variable label
deaw1	byte	%8.0g		Total number of death experienced in time period 1986
cataw1	byte	%8.0g		Total number of disasters experienced in time period 1976-1986
accdw2	byte	%8.0g		Total number of accidents experienced in time period 1987-1996
accdw3	byte	%8.0g		Total number of accidents experienced in time period 1996-NOW
cataw3	byte	%8.0g		Total number of disasters experienced in time period 1996-NOW
movew2	byte	%8.0g		Total number of moves experienced in time period 1987-1996

Table 13 Female major negative life events

Cox regression -- Breslow method for ties

No. of subjects =	186	Number of obs =	186
No. of failures =	182		
Time at risk =	2360		
Log likelihood =	-784.52046	LR chi2(5) =	27.01
		Prob > chi2 =	0.0001

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
deaw1	1.692344	.2263099	3.93	0.000	1.302151	2.199461
cataw1	1.810502	.3933043	2.73	0.006	1.182738	2.771467
accdw2	1.386542	.2780507	1.63	0.103	.9359163	2.054135
accdw3	1.650754	.3321571	2.49	0.013	1.112775	2.448822
cataw3	3.372636	2.434525	1.68	0.092	.8194696	13.88053

Test of proportional-hazards assumption

Time: Time

	chi2	df	Prob>chi2
global test	7.82	5	0.1667

Among the female respondents, a different pattern emerged. Table 13 reveals the findings for the female subsample. Below, we present the legend for Table 13, which follows. In Table 13, we present the risk factors related to time till the first onset of females experiencing depression. For both men and women, catastrophes (such as Chornobyl in 1986) explain the time till first onset of depression. For women deaths in wave and for men deaths in wave two also contribute to this explanation. Accidents in wave two are not quite as significant

as those in wave three for females. Deaths are always significant regardless of the wave. Neither of these models violates the proportional hazards assumption. The major negative life events proffers an  $R_D^2$  of 0.126 for the women, accounting for 14.17% of the total proportional reduction in error in the female model.

## 4.5 Stresses and hassles

The burden carried by an individual before lapsing into depression may not be solely from a cascade of catastrophe. It can come from an accumulation of protracted strain due to a confluence of daily stressors and hassles. Among the 10 major hassles in life is a move from one residence to another. Male respondents indicated that only stresses and hassles from relationships were potentially those that stemmed from relationships in 1986. This category of variables had a  $R_D^2$  of 0.0657, which explained only 7.635% of the total proportional reduction of error in the male model.

Table 14 Male daily stresses and hassles

Cox regression -- Breslow method for ties

No. of subjects =	154	Number of obs =	154
No. of failures =	152		
Time at risk =	1980		
Log likelihood =	-635.30891	LR chi2(1) =	2.71
		Prob > chi2 =	0.0998

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
shrelaw1	1.00367	.0022093	1.66	0.096	.9993496 1.00801

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
shrelaw1	-0.16842	4.29	1	0.0383
global test		4.29	1	0.0383

Because this variable interacts with time, we would have to transform it if this were to be our final model. We would refrain from using this sub-model by itself without further transformation of the stresses and hassles for males derived from their relationships in wave one. However, we are going to consider a larger model, consisting of this sub-model combined with others shortly, for which reason this limitation of the sub-model need not consume our attention now.

For females, Table 15 reveals that the significant impacts on the time till the first depression spell came from the job, possibly from moves in wave two, but more likely from housing issues but stresses and hassles had an  $R_D^2$  of 0.067, accounting for only 7.551% of the



Table 15 Female daily stresses and hassles

variable name		variable label				
shjobw1	byte	%8.0g	Percentage of strains and hassles related to job in 1986			
movew2	byte	%8.0g	Total number of moves experienced in time period 1987-1996			
shhousw3	byte	%8.0g	Percentage of strains and hassles related to housing NOW			
Cox regression -- Breslow method for ties						
No. of subjects =		186	Number of obs = 186			
No. of failures =		182				
Time at risk =		2360				
Log likelihood = -788.19555		LR chi2(3) = 19.66	Prob > chi2 = 0.0002			
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
shjobw1	1.005325	.0022979	2.32	0.020	1.000831	1.009839
movew2	1.4028	.2596858	1.83	0.067	.9759365	2.016368
shhousw3	1.005342	.0023097	2.32	0.020	1.000826	1.00988

. estat phtest, detail

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
shjobw1	-0.11635	2.72	1	0.0992
movew2	0.09612	1.71	1	0.1915
shhousw3	-0.07551	1.03	1	0.3090
global test		7.14	3	0.0676

total proportional reduction of error for the females. The proportional hazards regression assumption for the females is fulfilled and poses no problem for our using this sub-model by itself.

## 4.6 Buffers and Supports

Whereas stresses and hassles of daily life burden the individual and contribute to depression, they are counteracted somewhat by supports which buffer those effects. When we examine male respondents, the pre-eminent form of support stems from the family reported for the period of time prior to the interview, shown in Table 16. Thee *pseudo* -  $R^2$  for this sub-model = 0.046, which accounts for approximately 5.76% of the total proportional reduction of error, a proportion slightly less than that contributing to the male stresses and hassles.

Table 16 Buffers and supports for male respondents

Cox regression -- Breslow method for ties			
No. of subjects =	154	Number of obs =	154
No. of failures =	152		
Time at risk =	1980		
Log likelihood =	-632.61767	LR chi2(1) =	8.09
		Prob > chi2 =	0.0044

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
sufamw3	1.005586	.0019758	2.83	0.005	1.001721	1.009466

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
sufamw3	-0.08844	1.17	1	0.2794
global test		1.17	1	0.2794

By comparison, women may have obtained more support than men during the second wave—that is, the period from 1987 through 1996, and this may have come from the family during that time. However, there are several reasons to suspect that this support may have been somewhat tenuous: *pseudo* –  $R^2$  was a mere 0.0094, accounting for only 1.06% of the total proportional reduction of error, and the statistical levels of significance were not less than 0.05, notwithstanding the fulfillment of the proportional hazards assumption.

Table 17 Buffers and supports for female respondents

suprtw2	byte	%8.0g	Level of support (in percent) from partner in 1996			
sufamw2	byte	%8.0g	Level of support (in percent) from family in 1996			
Cox regression -- Breslow method for ties						
No. of subjects =		186	Number of obs =		186	
No. of failures =		182				
Time at risk =		2360				
			LR chi2(2) =		4.02	
Log likelihood =		-796.01746	Prob > chi2 =		0.1342	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
suprtw2	1.004734	.0025141	1.89	0.059	.9998182	1.009673
sufamw2	.9956006	.0027218	-1.61	0.107	.9902803	1.00095
Test of proportional-hazards assumption						
Time: Time						
	rho	chi2	df	Prob>chi2		
suprtw2	-0.00949	0.02	1	0.9017		
sufamw2	0.00301	0.00	1	0.9691		
global test		0.02	2	0.9906		

## 4.7 Self-perceived health assessment

The self-perceived health assessment includes specific types of illnesses mentioned as well as the self-reported quality of the health of the respondent. This includes both physical and mental health. Tables 18 and 19 present the data for the male and female self-reported health assessment, which consists of a general physical and mental health self-report, if one or the other is statistically significant, along with the self-reports of the type of illnesses that the respondent suffers.

The male respondents identified cardiovascular and respiratory problems as pre-eminent, especially as the illness of primary concern, in 1986. In the decade that followed, they indicated that their mental health seemed to be reasonably good, with an average percent of 87.89 and a standard deviation of 16.67. The

$R_D^2$  for this set of variables in the male model was 0.142, which accounted for about 16.5% of the total proportional reduction of error.

**Table 18 Self-reported health assessment of male respondents**

variable name	storage type	display format	value label	variable label
mhlthw2	byte	%8.0g		level of general psychological/mental health in 1996 for males
cardiovascular1w1	byte	%8.0g		primary cardiovascular condition in wave 1
respiratory1w1	byte	%8.0g		primary respiratory condition in wave 1

Cox regression -- Breslow method for ties				
No. of subjects =	40	Number of obs =	40	
No. of failures =	39			
Time at risk =	413			
Log likelihood =	-108.85728	LR chi2(3) =	10.05	
		Prob > chi2 =	0.0181	

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
cardiova-1w1	2.46601	1.035718	2.15	0.032	1.08266	5.61691
respirat-1w1	17.40503	16.3103	3.05	0.002	2.773394	109.229
mhlthw2	1.006864	.0135753	0.51	0.612	.9806052	1.033826

Test of proportional-hazards assumption				
Time: Time				
	rho	chi2	df	Prob>chi2
cardiova-1w1	-0.00967	0.00	1	0.9527
respirat-1w1	0.02313	0.02	1	0.8783
mhlthw2	-0.03044	0.04	1	0.8404
global test		0.06	3	0.9960

As for the female respondents, Table 19 reveals that their self-reports of their mental health status are significantly related to the time till first onset of level 25 depression. There appear to be three different combinations of symptoms that can be significant depending upon which symptoms appear and during which wave of the study they appear, which we display in the three panels of Table 19. Primary among these symptoms are those that appear in the first wave. By primary we mean of major importance to the respondent in that these were the first and foremost illnesses cited. These include peripheral vascular problems, respiratory problems, and rheumatological problems during wave 1. In panel 2, we observe that Another set of emerges as a combination of dermatological and respiratory problems that emerge as of secondary importance in wave 3. In panel 3, we display the most important and encompassing set of self-reported medical problems among females. These include those symptoms of primary concern in wave 1 along with the self-report of general physical health in wave

Table 19 Self-reported health assessment of female respondents: Panel 1

Cox regression -- Breslow method for ties						
No. of subjects =	56			Number of obs =	56	
No. of failures =	54					
Time at risk =	648					
Log likelihood =	-170.13165			LR chi2(3) =	10.76	
				Prob > chi2 =	0.0131	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
peripher-1w1	3.536546	1.946549	2.29	0.022	1.202458	10.40133
respirat-1w1	2.849314	1.249358	2.39	0.017	1.206447	6.729339
rheumato-1w1	3.469	1.778293	2.43	0.015	1.270158	9.474378

Table 19 Self-reported health assessment of female respondents: Panel 2

Cox regression -- Breslow method for ties						
No. of subjects =	122			Number of obs =	122	
No. of failures =	121					
Time at risk =	1451					
Log likelihood =	-471.45845			LR chi2(2) =	10.76	
				Prob > chi2 =	0.0046	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
dermatol-2w3	11.51334	8.83881	3.18	0.001	2.557008	51.84062
respirat-2w3	.4789706	.1781757	-1.98	0.048	.2310278	.9930096

Table 19 Self-reported health assessment of female respondents: Panel 3

Cox regression -- Breslow method for ties						
No. of subjects =	56			Number of obs =	56	
No. of failures =	54					
Time at risk =	648					
Log likelihood =	-167.49592			LR chi2(4) =	16.03	
				Prob > chi2 =	0.0030	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
peripher-1w1	3.258426	1.791191	2.15	0.032	1.109413	9.570227
respirat-1w1	2.884991	1.258535	2.43	0.015	1.226931	6.783733
rheumato-1w1	2.450852	1.294124	1.70	0.090	.8706763	6.89886
phlthw3	.9814799	.0079709	-2.30	0.021	.9659809	.9972276

---

Test of proportional-hazards assumption				
Time: Time				
	rho	chi2	df	Prob>chi2
peripher-1w1	0.00289	0.00	1	0.9832
respirat-1w1	0.06024	0.21	1	0.6453
rheumato-1w1	0.08398	0.38	1	0.5364
phlthw3	0.15631	1.26	1	0.2618
global test		1.61	4	0.8061

---

3. The test of the proportional hazards assumption for the most encompassing of these models and show that the assumption holds, which is shown at the bottom of panel three on the top of this page. Although the proportional hazards tests for panels 1 and 2 are not shown here, the models assumptions hold, with respective  $\chi^2 = 0.38$  with  $df = 3$  and  $p = 0.9443$  and a  $\chi^2 = 0.95$   $df = 2$  and  $p = .6222$ . If we select the third set, shown above, which happens to be the most encompassing of the syndromes, we note that this set of variables for the women has a  $R_D^2 = 0.18988$ , which is approximately 21.35% of the total proportional reduction of error.

#### 4.8 Medical diagnosis

When we examine the medical diagnosis reported for these respondents, we find that the multicollinearity between the self-reports and the medical diagnoses cause either the self-reports or the actual medical doctors icd9 codes to be dropped, owing to the almost 1:1 relationship between them. In other words, we can have either one or the other in the models at the same time but not both. We retain the medical diagnosis for several reasons. They are relatively objective, and they are more specific, and they are categorized the International classification of diseases, version nine, which has been incorporated into Stata, which permits a more careful analysis of this aspect of the respondent's health. The high correlation between these sets of items provides a measure of support the respondent's claims relating to their health.

Table 20 shows that prominent diagnoses among the males included gastritis/duodenitis, cholecystitis, and cerebral artery occlusion with infarction. When taken together, this set of symptoms also passes the proportional hazards assumptions, as can be seen from the results of the global test at the bottom of Table 20. The cerebral artery occlusion with infarction (stroke) is often followed by hemiplegia or aphasia according to this icd9 code. The pseudo- $R_D^2$  for this set of diagnoses is 0.156, or 18.21% of the total proportional reduction of error in the female model.

Continued on the next page...

Table 20 Medical diagnosis of prominent male health problems

variable name	type	format	label	variable label
icdx3nr9	byte	%8.0g		icdx3nr==gastritis/duodenitis
icdx3nr10	byte	%8.0g		icdx3nr==575.1 cholecystitis
icdx4nr9	byte	%8.0g		icdx4nr==434.91 crbrl art ocl nos w infarc

Cox regression -- Breslow method for ties

No. of subjects =	154	Number of obs =	154
No. of failures =	152		
Time at risk =	1980		
Log likelihood =	-631.37264	LR chi2(3) =	10.58
		Prob > chi2 =	0.0142

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
icdx3nr9	2.228061	.9335263	1.91	0.056	.9801345	5.064873
icdx3nr10	11.72413	12.17174	2.37	0.018	1.532432	89.69743
icdx4nr9	33.78582	37.10585	3.21	0.001	3.925435	290.7911

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
icdx3nr9	-0.06435	0.61	1	0.4345
icdx3nr10	0.01588	0.04	1	0.8454
icdx4nr9	0.00298	0.00	1	0.9707
global test		0.66	3	0.8826

Table 21 reveals that the women and men both have some of the same medical diagnoses. Both women and men have been given medical diagnoses of cholecystitis. Both have some form of arterial occlusion. For the women, this includes myocardial infarction rather than stroke. The women also have been diagnosed with hypertension and chronic pancreatitis. Like the set of diagnoses for the men, this set also passes the proportional hazards tests as revealed in by the lack of statistical significance of the  $\chi^2$  test at the bottom of Table 21. The pseudo- $R_D^2$  for the medical diagnoses of the female respondents is .1703, which accounts for 19.16% of total proportional reduction of error for the females.

Table 21 Medical diagnosis for female respondents

variable name	type	format	label	variable label
icdx3nr5	byte	%8.0g		icdx3nr==hypertension
icdx3nr11	byte	%8.0g		icdx3nr==577.1 chronic pancreatitis
icdx4nr7	byte	%8.0g		icdx4nr==acute myocardial infarct
icdx5nr5	byte	%8.0g		icdx5nr==hypertension
icdx5nr12	byte	%8.0g		icdx5nr==575.1 cholecystitis

Cox regression -- Breslow method for ties

No. of subjects =	186	Number of obs =	186
No. of failures =	182		
Time at risk =	2360		
Log likelihood =	-788.40871	LR chi2(5) =	19.23
		Prob > chi2 =	0.0017

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
icdx3nr5	2.081883	.6867055	2.22	0.026	1.090659	3.973962
icdx3nr11	3.363755	2.42621	1.68	0.093	.8182188	13.82864
icdx4nr7	55.56689	62.24548	3.59	0.000	6.184555	499.2564
icdx5nr5	3.363755	2.42621	1.68	0.093	.8182188	13.82864
icdx5nr12	5.248423	2.710823	3.21	0.001	1.907134	14.44363

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
icdx3nr5	-0.00086	0.00	1	0.9908
icdx3nr11	0.00967	0.02	1	0.8963
icdx4nr7	-0.00067	0.00	1	0.9929
icdx5nr5	0.00967	0.02	1	0.8963
icdx5nr12	-0.02356	0.10	1	0.7530
global test		0.14	5	0.9996

## 4.9 Health behaviors

Only one male health behavior appears to be related to the time till the first onset of depression. That is the use of any contraception during wave three—from 1997 to the present time of the interview. The details of this relationship are displayed in Table 22 on the next page. The *pseudo* -  $R^2$  for the men is only about 0.0572, accounting for 6.64% of the total proportional reduction of error in that model. Although the percentage impact on the time till the first onset of depression may be 61.4%, the basic assumption of proportional hazards is also fulfilled.



**Table 22 Health behaviors of male respondents**

variable name	type	format	label	variable label		
contw3	byte	%15.0g	LABC	use of any contraception method in 1997-now		
Cox regression -- Breslow method for ties						
No. of subjects =		154		Number of obs =		154
No. of failures =		152				
Time at risk =		1980				
Log likelihood =		-632.54994		LR chi2(1) =		8.23
				Prob > chi2 =		0.0041
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
contw3	1.614892	.268431	2.88	0.004	1.165882	2.236825
Test of proportional-hazards assumption						
Time: Time						
	rho	chi2	df	Prob>chi2		
contw3	-0.05168	0.41	1	0.5195		
global test		0.41	1	0.5195		

As for female health behaviors, the use of natural contraception is the health behavior that appears related to the time till first onset of level 25 depression. Reliance on natural contraception by the women accounts for a 0.12 % reduction of impact on the dependent variable. The pseudo- $R^2$  for this model for females is 0.0031, which is a mere 0.34% of total variance explained.

**Table 23 Health behaviors of female respondents**

Cox regression -- Breslow method for ties						
No. of subjects =		186		Number of obs =		186
No. of failures =		182				
Time at risk =		2360				
Log likelihood =		-797.66956		LR chi2(1) =		0.71
				Prob > chi2 =		0.3987
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
ncontw2	.8860257	.1267342	-0.85	0.398	.6694117	1.172734
Test of proportional-hazards assumption						
Time: Time						
	rho	chi2	df	Prob>chi2		
ncontw2	-0.06961	0.83	1	0.3623		
global test		0.83	1	0.3623		

Nonetheless, the proportional hazards assumption is not violated.

## 4.10 Health scale measurements

There are significant effects on the time to onset of depression that appear to be accounted for by problem solving coping, The Nottingham Health profile energy level and to a lesser extent by the emotional reaction scales, along with the Mississippi Post-traumatic stress syndrome (PTSD) scale. Problem solving coping, energy level, and PTSD appear to be significantly positively related to the time till first onset of level 25 depression. The emotional reaction scale is almost inversely significantly related to it. Most of these effects however have little impact on the dependent variable. Nevertheless, the proportional hazards assumption remains fulfilled and the pseudo- $R_D^2$  for this male model is approximately 0.101. This is about 11.78% of the total reduction of error in the male model.

**Table 24 Significant health scales of male respondents**

variable name	type	format	label	variable label		
CSavoid	byte	%9.0g		Coping Avoidance subscale		
WHPel	int	%9.0g		Wtd Health Profile Pt 1 Energy Level Subscale		
WHPer	float	%9.0g		Wtd Health Profile Emotional reaction Pt 1 subscale		
MiPTSD	byte	%9.0g		Mississippi post-traumatic stress disorder scale		
Cox regression -- Breslow method for ties						
No. of subjects =		153	Number of obs =	153		
No. of failures =		151				
Time at risk =		1978				
Log likelihood =		-620.2684	LR chi2(4) =	22.68		
			Prob > chi2 =	0.0001		
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
CSprbslv	1.049643	.0204408	2.49	0.013	1.010334	1.09048
WHPel	1.00781	.003101	2.53	0.011	1.00175	1.013906
WHPer	.9879022	.0064811	-1.86	0.064	.9752809	1.000687
MiPTSD	1.019473	.0076423	2.57	0.010	1.004604	1.034562

Test of proportional-hazards assumption

Time: Time

	rho	chi2	df	Prob>chi2
CSprbslv	-0.06764	0.72	1	0.3947
WHPel	0.02024	0.07	1	0.7936
WHPer	-0.12547	2.43	1	0.1193
MiPTSD	0.06122	0.41	1	0.5217
global test		3.21	4	0.5233

With women, PTSD is not always a stable phenomenon. As shown in Table 25, PTSD can be partially masked by anxiety and obsessive compulsiveness, along with interactions with them. However, when pain and its interaction with PTSD occur simultaneously, Table 26 shows how highly these are correlated and how those correlations can change when their interactions are added to the mix.

**Table 25 Significant health scales of female respondents**

Cox regression -- Breslow method for ties						
No. of subjects =		186	Number of obs =		186	
No. of failures =		182				
Time at risk =		2360				
Log likelihood = -787.53015			LR chi2(3) =		20.99	
			Prob > chi2 =		0.0001	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
MiPTSD	1.016642	.0167145	1.00	0.315	.984404	1.049935
BSIoc	1.106309	.0796857	1.40	0.161	.960651	1.274052
ptsdXoc	.9993537	.0011996	-0.54	0.590	.9970053	1.001708
Cox regression -- Breslow method for ties						
No. of subjects =		186	Number of obs =		186	
No. of failures =		182				
Time at risk =		2360				
Log likelihood = -787.36898			LR chi2(3) =		21.31	
			Prob > chi2 =		0.0001	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
MiPTSD	1.033518	.0183175	1.86	0.063	.998233	1.070051
BSIanx	1.215102	.105569	2.24	0.025	1.024848	1.440674
ptsdXanx	.9978934	.0014099	-1.49	0.136	.9951339	1.000661

At this juncture, it should be noted that the apparent instability of this relationship may be partially a artifact of the substantial correlation between these scales. When correlations among scales become large, the models become more fragile. The stability of the relationships may be an artifact of the high intercorrelations among the explanatory variables. Table 26 shows the Pearson product-moment correlations among some of these health scales. Adding interactions may aggravate this condition by increasing these correlations. For example, the correlation between MiPTSD and between obsessive-compulsiveness measured by the Basic Symptom inventory and is 0.633 and the correlation between anxiety and PTSD is .0.55. These correlations are not negligible. In fact, they are too high to be ignored.

When the interaction with PTSD are included, the correlation between the component and PTSD increases even more. For example, the correlation between obsessive-compulsiveness and PTSD rises from 0.55 to 0.8389 with its interaction term. Although the correlation between anxiety and PTSD used to be 0.55, when the interaction of PTSD and anxiety is added, the correlation between PTSD and that interaction approaches 0.798. the PTSD by anxiety interaction correlation with PTSD rises from 0.55 to 0.90. As the correlations among the explanatory variables rise, so do the magnitudes of their standard errors in the Cox regression models. This increase in their standard errors, in turn, renders these parameter estimates less statistically significant. Such conditions lead to unstable but potential interrelationships that have to be properly qualified.

Table 26 Pearson product-moment correlations among health scales

	MiPTSD	BSIoc	BSIanx	WHPpain	ptsdXpain	ptsdXoc	ptsdXanx
MiPTSD	1.0000						
BSIoc	0.6330 0.0000	1.0000					
BSIanx	0.5500 0.0000	0.6433 0.0000	1.0000				
WHPpain	0.4125 0.0000	0.4707 0.0000	0.4502 0.0000	1.0000			
ptsdXpain	0.5630 0.0000	0.5352 0.0000	0.5203 0.0000	0.9607 0.0000	1.0000		
ptsdXoc	0.8389 0.0000	0.9309 0.0000	0.6567 0.0000	0.4777 0.0000	0.6030 0.0000	1.0000	
ptsdXanx	0.7983 0.0000	0.6931 0.0000	0.9190 0.0000	0.4797 0.0000	0.6138 0.0000	0.8134 0.0000	1.0000

**Table 27 Significant health scales of female respondents**

Cox regression -- Breslow method for ties						
No. of subjects =	186			Number of obs =	186	
No. of failures =	182					
Time at risk =	2360					
				LR chi2(3) =	16.48	
Log likelihood =	-789.78473			Prob > chi2 =	0.0009	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
MiPTSD	1.028712	.0108541	2.68	0.007	1.007656	1.050207
WHPpain	1.0353	.0176512	2.03	0.042	1.001276	1.07048
ptsdXpain	.9994739	.0003086	-1.70	0.088	.9988693	1.000079
Test of proportional-hazards assumption						
Time: Time						
	rho	chi2	df	Prob>chi2		
MiPTSD	-0.13941	4.12	1	0.0423		
WHPpain	-0.10334	2.09	1	0.1484		
ptsdXpain	0.09645	1.88	1	0.1705		
global test		5.84	3	0.1197		

Therefore, we can say from Table 27 that under such conditions, it is possible that PTSD and anxiety may catalyze one another to emerge as statistically significant as shown. The assumption of proportional hazards is fulfilled and it is possible that the enhanced multicollinearity is contributing to the reduced statistical significance of the interaction term. When these variables are combined together, PTSD has a 2.87% rise on effect of the dependent variable, but the  $R_D^2$  for this model is only 0.0624, representing 7.02% of the total reduction of error in the female model.. Therefore, these findings appear possible but may be an artifact of the high intercorrelation among the explanatory variables of the model.

#### 4.11 General risk awareness

General risk awareness on the part of male respondents indicates that several components are positively related to the time to first onset of level 25 depression. These components include concerns about the hazardous effects of radiation, implications of the economic conditions in the country since 1997, along with the level of trust in the 1986 governmental reports about Chornobyl. All of these factors appear to be significantly positively related to the dependent variable.

Two factors are significantly negatively related to the time till first appearance of that depression. They are deficiencies in essential nutrition and the implications of the political problems plaguing the country at the time. Whether these factors are positively or negatively related to the dependent variable, the model does not violate the proportional hazards assumption. These results are

shown in Table 28 below.

The change measured in percent of the dependent variable brought about by these effects are 1.4% due to the effects of radiation, 1.8% due to the economic problems of the country since 1997, and 0.5% due to the trust in the 1986 governmental reports about Chornobyl. The negative impacts on the dependent variable were 1.83% due to nutritional deficiencies in essential foods and 1.03 % due to political problems in the country in recent or current times. The  $R_D^2$  for this set of variables in the male model is 0.0528, which is approximately 6.13% of the total error reduction in the male model.

**Table 28 General male risk awareness**

variable name	type	format	label	variable label
defnw2	byte	%8.0g		* consider hazardous (in percent) - deficiencies in essential nutrition in 1996
efradw2	byte	%8.0g		consider hazardous (in percent) effects of radiation in 1996
ecprw3	byte	%8.0g		consider hazardous (in percent) - economic problems, NOW
polprw3	byte	%8.0g		consider hazardous (in percent) - political problems NOW
trgovw1	byte	%8.0g		level of trust in government reports about chornobyl in time period 1976-1986
Cox regression -- Breslow method for ties				
No. of subjects =		139		Number of obs = 139
No. of failures =		137		
Time at risk =		1877		
Log likelihood =	-554.04914			LR chi2(5) = 13.34 Prob > chi2 = 0.0204

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
defnw2	.9816901	.0077102	-2.35	0.019	.9666941	.9969187
efradw2	1.014139	.0051729	2.75	0.006	1.004051	1.024329
ecprw3	1.018219	.008312	2.21	0.027	1.002057	1.034641
polprw3	.9896777	.0049962	-2.06	0.040	.9799336	.9995187
trgovw1	1.005287	.0022805	2.32	0.020	1.000828	1.009767

Test of proportional-hazards assumption				
Time: Time				
	rho	chi2	df	Prob>chi2
global test		0.94	5	0.9673

General female risk awareness becomes apparent in the positive relationship between the dependent variable and a belief that radiation poses a threat to the pregnancy of a woman, that the political problems from 1987 through 1996 pose a danger to people and that the percentage of area contaminated by radiation poses a threat to man.

According to Table 29, the parameter estimates for these risk factors are presented. The percentage change in the dependent variable effected can be quantified as 0.68% by the neonatal danger to the pregnancy, the 0.4% by the political problems in the decade following Chornobyl, and 0.43% by the percentage of contaminated area.

The  $R_D^2$  for this set of variables is 0.0456 which is approximately 5.134% of the total reduction of error indicated in the female model. The proportional hazards assumption holds for this submodel as well.

**Table 29 General female risk awareness**

Cox regression -- Breslow method for ties						
No. of subjects =	186			Number of obs =	186	
No. of failures =	182					
Time at risk =	2360					
Log likelihood =	-790.4608			LR chi2(3) =	15.13	
				Prob > chi2 =	0.0017	
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
woman	1.006807	.0026148	2.61	0.009	1.001695	1.011945
polprw2	1.003977	.0019707	2.02	0.043	1.000122	1.007847
radw2	1.004335	.0022169	1.96	0.050	.999999	1.008689
Test of proportional-hazards assumption						
Time: Time						
			chi2	df	Prob>chi2	
global test			3.97	3	0.2646	

## 4.12 Chornobyl related danger and injury

Before trying to combine all of these sets into an omnibus model, we have to consider those parameters relating to Chornobyl and injury and suffering caused by it. We examine the male reports first.

Among the male reports, three variables appear to be related to the time till first onset of level 25 depression. First, the belief in the percent of the radioactively contaminated area is one of these variables Second, the percent of pollution related to Chornobyl is related and third, the lifetime exposure to radiation is statistically significantly related to the dependent variable.

The percentage change in the dependent variable effected by these variables is 0.9% for the belief in the percentage area contaminated, 011% for the belief in the % of area contaminated by Chornobyl, and 0.73% for the belief in the lifetime exposure to radiation. The  $R_D^2$  for this male submodel was 0.0972, representing 11.302% of the total reduction in error effected by these variables. The assumption of the proportional hazards remains fulfilled for the males.

**Table 30 Chornobyl related issues and injury for males**

variable name	type	format	label	variable label		
radw2	byte	%8.0g		believed % of the radioactively contaminated area in 1996		
radtlw3	byte	%8.0g		believed % of cumulative radiation exposed to in a lifetime NOW		
radchw2	byte	%8.0g		believed % of pollution related to chornobyl in 1996		
Cox regression -- Breslow method for ties						
No. of subjects =		149	Number of obs = 149			
No. of failures =		147				
Time at risk =		1905				
			LR chi2(3) =	19.36		
Log likelihood = -601.23062			Prob > chi2 =	0.0002		
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
radw2	1.009665	.0029245	3.32	0.001	1.003949	1.015413
radchw2	.9892434	.0032574	-3.28	0.001	.9828796	.9956483
radtlw3	1.007286	.0031668	2.31	0.021	1.001099	1.013512
Test of proportional-hazards assumption						
Time: Time						
	rho	chi2	df	Prob>chi2		
global test		0.73	3	0.8655		

Table 31 shows the results for the female respondents concerning the Chornobyl related issues and injury.



Females reported a fear of going outside after 1986. This seemed to be the predominant effect of Chornobyl on the dependent variable. This fear accounted for a 0.9% impact on the dependent variable. However, this fear was correlated with the time variable which violated the proportional hazards assumption. Fractional polynomial transformations did not have a remediable effect on the fulfillment of this basic assumption. We will pay closer attention to fulfillment of this assumption with respect to the omnibus models. This set of issues, taken separately, yielded an  $R_D^2 = 0.0619$ , representing 6.96% of the total reduction of error accounted for by the sets of variables.

**Table 31 Chornobyl related issues and injury for females**

variable name	type	format	label	variable label
goferw2	byte	%8.0g		level of fear in percent from going outdoors in 1987-1996
radchw3	byte	%8.0g		believed % of pollution related to chornobyl NOW
radchw3	byte	%8.0g		believed % of pollution related to chornobyl NOW
toxic	byte	%8.0g		all radioactive materials remain toxic for thousands of years (% of agreement)

Cox regression -- Breslow method for ties				
No. of subjects =	185	Number of obs =	185	
No. of failures =	181			
Time at risk =	2347			
Log likelihood =	-789.56575	LR chi2(3) =	6.50	
		Prob > chi2 =	0.0896	

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
toxic	.9985424	.0023031	-0.63	0.527	.9940385	1.003067
goferw2	1.009286	.0033927	2.75	0.006	1.002659	1.015958
radchw3	1.000491	.0023034	0.21	0.831	.9959861	1.005015

Test of proportional-hazards assumption				
Time: Time				
		chi2	df	Prob>chi2
global test		7.05	3	0.0702

### 4.13 Recapitulation

Before we try to put the contributions made by these variables and the classes of them into perspective, we need to discuss the  $R_D^2$  measure of explained variation in proportional hazards regression models. This measure, referred to as D, was propounded by Royston and Sauerbai in 2004 [15, 723-748]. The formula for this measure is given by

$$R_D^2 = \frac{D^2/\kappa^2}{\sigma^2 + D/\kappa} \quad (24)$$

where  $D^2/\kappa^2$  = variance of the parameter vector,  $\sigma^2$  = error variance. Therefore  $R_D^2$  is analogous to an intraclass correlation coefficient for Cox proportional hazards regression models, providing an estimate of the proportion of variance explained.  $\kappa$  is a scaling factor approximately equal to  $\pi/6$  for Cox regression models.

The  $R_D^2$  pseudo  $R^2$ , tabulated in Table 32, represents a relative improvement of fit from a particular starting point of the log-likelihood of the intercept only model. If the models are not nested, the pseudo- $R^2$  may not be properly comparable. To our measure provides for a within gender comparison, much as a  $\beta$  coefficient would in an ordinary least squares regression model.

The improvement of fit is compared to the model with only the intercept included. This intercept only model may differ between males and females. The model for the males will have a log-likelihood of 636.66, whereas that for the females will have a log-likelihood of 798.03. The basis of comparison differs between models, rendering cross-gender model comparisons improper.

To normalize these measures, a total was computed by adding up the components. The total was included at the bottom of the table. To obtain the percent for the males and the percent for the females, each coefficient was divided by the total and multiplied by 100. By comparing the percents within the gender, we can obtain a sense of how much each set of variables contributed to the total  $R_D^2$  of each gender.

The caveat is that multicollinearity often forced out of consideration some of the variables that we initially included. This wrought havoc on the nesting of the variables, for which reason the full omnibus model at the end of the analysis does not contain all of the variables in each of the categories for that gender. Hence, the Table 32 totals do not necessarily equal the total  $R^2$  for the final model. For this reason, we validate the adjusted  $R^2$  for the omnibus male and female models with a bootstrap program written by Patrick Royston of the Medical Research Council (clinical trials unit) in the United Kingdom. The validated adjusted  $R^2$  are entered at the bottom of Table 32. It is merely used to show the basis upon which the percents were computed for internal comparison only.

Because the total in Table 32 is equal to the additive sum of the  $R_D^2$  for the categories and because the total may not be equal to the sum of its parts, due to the overlap of explained variance among the explanatory variables, we use Patrick Royston's str2ph program to validate the goodness of fit of the Cox regression model. Using Royston's program, str2ph.ado, we find that the adjusted  $R^2$  explaining the variation is equal to 0.2779 for the males and 0.2875 for the females, whereas the  $R$  for the males equals 0.3795 and for the females equals 0.3479.

For the males, the medical diagnosis accounted for a plurality of the improvement for each category. Self-perceived ills accounted for the second greatest

improvement of fit. Major negative life events comprised the third largest set of variables improving the goodness of fit. The health scales—namely, the BSI, the Mississippi PTSD scale, Nottingham health profile and the coping scales – represented the next largest class of variables improving the fit. the heals of those, but almost tied for fourth place was radiation and Chornobyl issues. These by far were the classes of variables linked closely to the time till the first onset of substantial depression.

For the females, self-perceievd health assessment and illnesses represented the set of which improved the fit the most. In second place was the medical diagnoses of the doctors. In third place were socio-demographic variables. In fourth place were the major negative life events. The remaining sets of variables accounted for much less improvement of fit.

Table 32 R2D pseudo-  $R^2$  for male and female models

category	maleR2d	malePct	femaleR2d	femalePct
geosociodem	.0296757	3.449698	.1534649	17.25876
MajNegEvts	.1088522	12.6537	.1260008	14.17013
StrsHasls	.0656839	7.635536	.0671456	7.551235
BufsSpts	.0495838	5.76395	.0094289	1.060377
SlfPcdIlls	.1415528	16.45503	.1898281	21.34819
MedDx	.1566642	18.21169	.1703331	19.15576
HlthBhv	.0571961	6.648854	.0030842	.3468461
HlthScls	.1013579	11.78251	.0624162	7.01937
risksavy	.0528105	6.139037	.0456509	5.133924
radissues	.0972273	11.30234	.0618984	6.961133
Total	0.8602	100 %	0.8893	100 %
Royston's $R^2$	0.3795		0.3479	
Royston's adj. $R^2$	0.2779		0.2875	

#### 4.14 Omnibus Cox Regression model for males

We want to see which of the variables are retained in the model when all of the variables are entered simultaneously We call the resulting model omnibus models and present them for both men and women. After that, we compare a set of accelerated failure time models and find that the Weibull regression for the males and a gamma regression for the females yields the best fitting models. First, we examine the trimmed omnibus Cox regressions for the males and the females. Notwithstanding the omnibus nature of this model, it had to be pruned of statistically nonsignificant parameters for reasons of economy of statistical power and parsimony.

The Cox statistical regression model for the males appears not to violate the proportional hazards assumption, as is shown at the bottom of Table 33. The model appears to fit quite well according to Harrell's concordance statistic between the observed and the predicted values, with  $C = 0.784$ . The Somer's D

measurement of this fit = .5681, so the model not only fulfills the assumption test, it also appears to fit reasonable well. This omnibus model therefore merits more detailed attention.

Among the males we observe that particular geographic areas are associated with enhanced or reduced depression scores. All of these areas had their own area codes and all but Taraschanskiy were positively associated with the time till the first onset of level 25 depression. If the respondent lived in Taraschanskiy region, this was associated with about a 0.94% reduction in the magnitude of the time till onset of level 25. Living in Zhitomyrsiky, in contrast is associated with an increase of approximately 168% of the time till such depression. This may have been due to the fact that many of those moved out of the exclusion zone were moved to this area. It may also have been due to part of region may have been downwind of the radioactive plume for awhile.

Among the statistically significant socio-demographic variables are age, being married in 1986, being widowed in 1986, being divorced during the decade after 1986, or having an occupation as a factory laborer, or working in transportation or cleaning in wave three. Having suffered a divorce in the decade after 1986 was associated with a 399% increase in the dependent variable. An increase of one year of age is associated with a 6.16% change in the dependent variable. Being divorced in 1986, which is linked to a decrease in the dependent variable of 72.5%, is almost statistically significant at  $p = 0.056$ .

The only major negative life event associated with the dependent variable appears to have been a catastrophe in wave three, which is linked to a 0.994% decrease in the dependent variable.

Five daily stresses and hassles are significantly related to the time till such depression emergence. Stresses and hassles from relationships and from the job appear to be positively related to the time till depression, whereas stresses and hassles from family and housing appear to be negatively related to this span of time. But the impact from relationships only accounts for about a 1.6% increase in the dependent variable.

Table 33 Explanatory variables in the male Omnibus Cox regression model

variable name	type	format	variable label
Korostenskiy	byte	%8.0g	ranown==69
Narodichevskiy	byte	%8.0g	ranown==78
Radomischevskiy	byte	%8.0g	ranown==86
Tarascheskiy	byte	%8.0g	ranown==93
Zhitomirskiy	byte	%8.0g	ranown==102
age	byte	%8.0g	* Respondent's age
mar3w1	byte	%9.0g	Married in 1986
mar5w1	byte	%9.0g	Divorced in wave 1
occ5w3	byte	%15.0g	factory laborer machinist transp cleaner now
dvcew2	byte	%8.0g	Total number of divorces experienced in time period 1987-1996
cataw3	byte	%8.0g	Total number of disasters experienced in time period 1996-NOW
shfamw1	byte	%8.0g	Percentage of strains and hassles related to family in 1986
shrelaw1	byte	%8.0g	Percentage of strains and hassles related to relationships in 1986
shjobw2	byte	%8.0g	Percentage of strains and hassles related to job in 1996
shhlw2	byte	%8.0g	Percentage of strains and hassles related to health in 1996
shhousw3	byte	%8.0g	Percentage of strains and hassles related to housing NOW
suprtw1	byte	%8.0g	Level of support (in percent) from partner in 1986
suchrw1	byte	%8.0g	Level of support (in percent) from Chernobyl survivor benefits in 1986
mhlthw2	byte	%8.0g	level of general psychological/mental health in 1996
mhlthw3	byte	%8.0g	level of general psychological/mental health now
icdx3nr6	byte	%8.0g	icdx3nr==acute myocardial infarct
ncontw1	byte	%15.0g	use of natural contraception in 1976-1986
MiPTSD	byte	%9.0g	Mississippi post-traumatic stress disorder scale
defnw1	byte	%8.0g	* consider hazardous (in percent) - deficiencies in essential nutrition in 1986
defnw2	byte	%8.0g	* consider hazardous (in percent) - deficiencies in essential nutrition in 1996
efradw3	byte	%8.0g	consider hazardous (in percent) - effects of radiation NOW
ecprw3	byte	%8.0g	consider hazardous (in percent) - economic problems, NOW
trgovw1	byte	%8.0g	level of trust in government reports about chornobyl in time period 1976-1986

Table 34 Omnibus male Cox Proportional hazards regression model

Cox regression -- Breslow method for ties

No. of subjects = 138 Number of obs = 138  
 No. of failures = 136  
 Time at risk = 1871  
 LR chi2(28) = 94.69  
 Log likelihood = -508.16552 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Korostenskiy	2547.232	3465.215	5.77	0.000	177.0546	36646.27
Narodichev-y	30.74272	40.66074	2.59	0.010	2.301079	410.7268
Radomische-y	28.50788	36.79579	2.60	0.009	2.271429	357.7921
Taraschnskiy	.0590859	.0650946	-2.57	0.010	.006819	.5119747
Zhitomirskiy	2.680468	.9326266	2.83	0.005	1.355341	5.301183
age	1.061576	.0187196	3.39	0.001	1.025514	1.098908
mar3w1	.3640617	.1359438	-2.71	0.007	.1751173	.7568694
mar5w1	.2753806	.1860833	-1.91	0.056	.0732402	1.035421
occ5w3	.2824997	.1235527	-2.89	0.004	.1198783	.6657258
dvcew2	4.986525	3.274371	2.45	0.014	1.376771	18.06068
cataw3	.0060443	.0076461	-4.04	0.000	.0005065	.072131
shfamw1	.9874573	.0039896	-3.12	0.002	.9796686	.9953078
shrelaw1	1.016219	.0044466	3.68	0.000	1.007541	1.024972
shjobw2	1.007412	.0038565	1.93	0.054	.9998821	1.014999
shhlw2	.9898465	.0041637	-2.43	0.015	.9817194	.998041
shhousw3	.9902823	.0036482	-2.65	0.008	.9831577	.9974585
suprtw1	1.032123	.0195893	1.67	0.096	.9944345	1.071241
suchrw1	.9710358	.0153686	-1.86	0.063	.9413763	1.00163
mhlthw2	.9679392	.0065782	-4.79	0.000	.9551317	.9809185
mhlthw3	1.021049	.0063609	3.34	0.001	1.008658	1.033592
icdx3nr6	.0013066	.0021522	-4.03	0.000	.0000518	.0329765
ncontw1	1.80818	.4561703	2.35	0.019	1.102806	2.964722
MiPTSD	1.0577	.0117622	5.04	0.000	1.034895	1.081006
defnw1	.9890603	.0048379	-2.25	0.025	.9796234	.998588
defnw2	.9846339	.0069572	-2.19	0.028	.971092	.9983645
efradw3	1.014134	.0040878	3.48	0.000	1.006153	1.022177
ecprw3	1.011382	.0071	1.61	0.107	.9975618	1.025394
trgovw1	1.012962	.003036	4.30	0.000	1.007029	1.01893

Test of proportional-hazards assumption

Time: Time

	chi2	df	Prob>chi2
global test	23.99	28	0.6821

Harrell's C concordance statistic

Harrell's C = (E + T/2) / P = .784  
 Somers' D = .5681

It should also be noted that stresses and hassles from health related matters accounts for a less than 2 % decline in the dependent variable. All of these effects were significant at the 0.05 level except that of the stresses and hassles from the job, which has a p-value of 0.054.

Two effects may have comprised buffers and supports for the male respon-

dents. They were almost but not quite significant at the 0.05 level. They were support from a partner and support as a Chornobyl survivor. Partner support is linked to a 3.2% increase whereas survivor support is associated with a 0.029 % decrease in support both during 1986.

As for the self-reported health of the men, mental health in wave two accounted for almost a 3.3% decline in the time to such depression, whereas the mental health condition during recent years (wave three) is clearly linked to a 2.1 % increase in the time to level 25 depression. An acute heart attack (myocardial infarction) is clearly linked to a significant 99% decrease in the time to level 25 depression.

The health behavior that appears to be significant for males is the use of natural conception methods which is linked to a 80.8% increase in the time till level 25 depression.

As for the health scales, we observe PTSD among the men is significantly associated with the time till onset of first level 25 depression. There is a statistically significant 5.8% increase in this time that is associated with PTSD among the male respondents.

The remaining variables that appear to account for this time span are those related to risk awareness and Chornobyl related danger. They include concern about sufficiency of nutrition during waves one and two, fear of the hazardous effects of radiation now and possibly fear of the implications of economic problems now as well trust in the governmental reports about Chornobyl in 1986. Only the economic matters are not significant at the 0.05 level. Only the concerns about sufficiency of nutrition are negatively related to the level 25 depression. Concern about nutritional sufficiency in 1986 was associated with 1.1% decrease in the time span till such depression onset. In the decade following that this concern is associated with a 1.5% decrease in the time till such onset. The belief in the hazardous effects of the radiation now are related to a 1.4% increase in the time span till such depression, economic problems now are related to a 1.1% increase in this interim, whereas the level of trust placed in governmental reports about Chornobyl in 1986 accounts for a 1.3% increase in that time delay.

## 4.15 Omnibus Cox proportional hazards regression model for females

Table 35 provides the variable labels for the explanatory variables contained within the Omnibus Cox proportional hazard regression model for female respondents and the following table displays the results of that analysis.

Table 35 Explanatory variables used in the female Cox regression analysis.

variable name	type	format	label	variable label
Irpenskiy	byte	%8.0g		ranown==67
Kyivskiy	byte	%8.0g		ranown==72
age	byte	%8.0g		* Respondent's age
mar2w1	byte	%9.0g		cohabiting in 1986
occ5w1	byte	%15.0g	LABJ	factory laborer machinist transp cleaner in 1986
occ4w2	byte	%15.0g	LABJ	precision prod mechan craft construction in 1996
occ5w2	byte	%15.0g	LABJ	factory laborer machinist transp cleaner in 1996
deaw1	byte	%8.0g		Total number of death experienced in time period 1986
cataw1	byte	%8.0g		Total number of disasters experienced in time period 1976-1986
icdx3nr9	byte	%8.0g		icdx3nr==gastritis/duodenitis
icdx4nr7	byte	%8.0g		icdx4nr==acute myocardial infarct
icdx4nr9	byte	%8.0g		icdx4nr==434.91 crbrl art ocl nos w infarc
icdx5nr2	byte	%8.0g		icdx5nr==thyrotoxicosis
icdx5nr11	byte	%8.0g		icdx5nr==gastritis/duodenitis
injothr	byte	%9.0g	inj	Was anyone u know injured by Chornobyl accident?
contw2	byte	%15.0g	LABC	use of any contraception method in 1987-1996
WHPer	float	%9.0g		Wtd Health Profile Emotional reaction Pt 1 subscale
BSIoc	byte	%9.0g		Basic Symptom Inventory Obsessive compulsive subscale
BSIanx	byte	%9.0g		Basic symptom inventory Anxiety subscale
HP2work	byte	%9.0g	hp2fmt	Nottingham Health profile subscale Part2: paid employment
neiwl	byte	%8.0g		level of danger by neighbors (in percent) in 1986
toxic	byte	%8.0g		all radioactive materials remain toxic for thousands of years (% of agreement)
. // nb: icdx3nr9 = gastritis duodenitis				
. // nb: icdx4nr7 = myocad infarction				
. // nb: icdx4nr9 = cerebral artery occlusion w infarction				
. // nb: icdx5nr12 = cholecystitis				
. // nb: icdx5nr11 = gastritis duodenitis				



Table 36 Omnibus female Cox proportional hazards regression model

Cox regression -- Breslow method for ties						
No. of subjects =	186				Number of obs =	186
No. of failures =	182					
Time at risk =	2360					
					LR chi2(22) =	114.66
Log likelihood =	-740.69403				Prob > chi2 =	0.0000
_t	Haz. Ratio	Std. Err.	z	P> z	[95% Conf. Interval]	
Irpenskiy	.2099189	.1186485	-2.76	0.006	.0693335	.6355652
Kyivskiy	.5906375	.1095523	-2.84	0.005	.4106189	.8495776
age	1.015977	.0080362	2.00	0.045	1.000348	1.03185
mar2w1	8.298633	5.156921	3.41	0.001	2.455017	28.05166
occ5w1	.0190842	.0226222	-3.34	0.001	.0018693	.1948394
occ4w2	.4124851	.1618752	-2.26	0.024	.1911453	.890129
occ5w2	34.66535	37.33738	3.29	0.001	4.198391	286.2255
deaw1	1.675044	.2579252	3.35	0.001	1.238674	2.265141
cataw1	2.79702	.7162107	4.02	0.000	1.693304	4.620149
icdx3nr9	40.87909	66.55443	2.28	0.023	1.681423	993.8606
icdx4nr7	45.64662	55.05933	3.17	0.002	4.292223	485.4394
icdx4nr9	75.4339	92.86337	3.51	0.000	6.756	842.2547
icdx5nr2	174.8943	273.7974	3.30	0.001	8.132374	3761.264
icdx5nr11	.0492925	.0526092	-2.82	0.005	.0060856	.3992601
injothr	1.620654	.4500906	1.74	0.082	.9403578	2.793105
contw2	2.072071	.3741065	4.04	0.000	1.454529	2.951798
WHPer	.9861731	.0053288	-2.58	0.010	.975784	.9966729
BSIoc	1.100168	.0274174	3.83	0.000	1.047722	1.15524
BSIanx	1.084312	.0293758	2.99	0.003	1.028239	1.143444
HP2work	.6461041	.1270554	-2.22	0.026	.4394556	.9499265
neiwl	1.004753	.0024777	1.92	0.054	.9999087	1.009621
toxic	.9936079	.0026478	-2.41	0.016	.9884318	.9988111

Test of proportional-hazards assumption

Time: Time

	chi2	df	Prob>chi2
global test	9.83	22	0.9878

Harrell's C concordance statistic

Number of subjects (N) = 186

Number of comparison pairs (P) = 15940

Number of orderings as expected (E) = 12091

Number of tied predictions (T) = 0

$$\text{Harrell's } C = (E + T/2) / P = .7585$$

Somers' D = .5171

The omnibus female proportional hazards model appears to be a well-founded model. It fulfills the fundamental assumption of the proportional hazards, as shown at the bottom of Table 36 with a  $\chi^2$  global test = 9.83, with 22 degrees of freedom, and a nonsignificant probability of an alternative hypothesis of a significant interaction with time as  $p=0.9878$ . Finally, the model fits reasonably

well with a Harrell's  $C = 0.7585$  and a Somer's  $D = 0.5171$ . The model therefore merits a more detailed examination.

Although many of the sociodemographic variables in the female model are also in the male model, most of the other explanatory variables are different. For example, the geographic variables are not the same. In the female omnibus model, the areas that emerge as statistically significant are those of Irpenskiy and Kievskiy, and both of these areas are associated with a decrease in the time span until first onset of level 25 depression.

However, age, cohabiting in 1986, an occupation as one involved in factory labor, transportation or cleaning in 1986 or in the decade thereafter, or precision production, craftsmanship, or construction in wave two are variables that appear to be related to the time till first onset of such depression. Among these variables, the precision craftsmanship seems to be most strongly related to an increase in the time span till first onset of level 25 depression. Cohabiting in 1986 seems to be related to an increase second only to that of being a precision production or craftsman. Age seems to be third among the variables that increase this time delay. Being a factor worker, being involved in transportation, or cleaning whether in waves one or two appears to be related to shortening the time till that depression.

Among the women, major negative life events either of catastrophic nature or entailing a death are significantly positively related to the onset of the level 25 depression. Catastrophes are associated with a 180% increase in the hazard whereas deaths are linked to a 67.5% increase.

For women respondents, medical diagnosis of particular illnesses are all significantly positively related to the time till depression onset at level 25. All of the medical diagnoses are statistically significant at the 0.01 level, except that of gastritis/duodenitis which is significant at the 0.05 level. Pre-eminent among the medical diagnoses is thyrotoxicosis, which has the most powerful effect on the dependent variable from a unit increase in an explanatory variable as the fifth disease cited. A diagnosis of thyrotoxicosis in this instance is associated with an increase of 17,389% change in the log relative odds of the onset of level 25 depression. The second most powerful explanatory variable in this regard is another diagnosis for the fourth disease diagnosed. It is a diagnosis of an cerebral arterial occlusion with infarction—in short, a cerebral embolism or stroke). The percentage change in the log relative odds associated with such a diagnosis is 7443.9%. The third most depressing explanatory variable is a diagnosis of a heart attack, for the fourth disease diagnosed, which disease is associated with a 4563.67% change in the imminence of onset of level 25 depression. Although the fourth most depressing diagnosis is that of gastritis or duodenitis, this is diagnosed either as the third or fifth disease. Either way, it is often followed by acid reflux and lack of rest coming from it. This accounts for about a 3988% rise in the log relative odds of depression when cited as the third disease and as a reduction in the log odds when reported as the fifth disease diagnosed.

The only health behavior apparently related to the onset of depression is that of the use of contraception in wave two. The use of contraception appears to be positively linked to a 107.21% increase in the log relative odds of level 25

depression imminence.

The health scales significantly associated with this dependent variable are the basic symptom inventory (BSI) obsessive-compulsiveness, BSI anxiety, Nottingham weighted health profile emotional reaction scale, and the Nottingham part 2 impact on work scale

Among the variables relating to risk awareness and Chornobyl related problems are a belief that all radioactive materials remain radioactive for thousands of years, the possible percent belief in the danger posed by the neighbors in wave one, and the possible belief that the female respondent was responsible for injuring another as a result of Chornobyl. We preface two of these variables with possible when the significance level was less than .10 but more than 0.05. For both the concern that the neighbors posed a danger and that another may have been injured due the respondent's speech or actions the significance level was above 0.05 but below 0.10. What was more certain was the belief on the part of the female respondent that all radioactive materials remained radioactive for thousands of years was related to a decrease in the hazard ratio pertaining to the imminence of the depression.

In sum, it is perhaps important that PTSD is found to be a significant explanatory variable on the part of the males and that further investigation of PTSD is therefore warranted. It is important that thyrotoxicosis is found to be a significant medical diagnosis among the women. This could be related to the iodine isotope number 131 ( $I^{131}$ ) fallout to which the residents were subjected when the government failed to disclose the release of the  $I^{131}$  in the atmosphere in time to distribute and administer to the infant public potassium iodine pills which would prevent their infant thyroid glands from overexposure to radioactivity from the  $I^{131}$  polluting the atmosphere. With a half-life of only 8 days, all these infants had to do was to avoid drinking milk for that a little more than a week to reduce the incidence of thyroid cancer that emerged some time thereafter. What we learned from this tragic error is a lesson for all nuclear disasters in the future, that the public should be immediately advised on what to do to and what not to do to mitigate the threat of cancer and other dangers following from exposure to fallout from such a catastrophe. The long-run legitimacy of the governmental leaders will be enhanced by their doing what is right to protect the public from such harm. Eventually, the public will learn about what was done and it behooves those in power to do what is right to protect innocent bystanders from environmental harm. It is also noteworthy that valid models explaining the relative hazard of depression can be developed to help us mitigate such damage in the future.

#### 4.16 Accelerated failure time models

Accelerated failure time models are parametric event history models whose dependent variable is usually  $\ln(t)$  where  $t$  = time till an event. When the error distribution can be formulated, these models provide a more accurate way of estimating parameters. They are appropriate for time till a single event, situations with gaps, time-varying covariates, and even multiple event data [18,

363].

If we wish to predict or forecast, it would be helpful to try to develop parametric models that prescribe or explain the time till onset of the depression. We test a set of models and find that the best fitting parametric models. We compared the exponential, lognormal, Weibull, log-logistic, gompertz and gamma models for males and females with a Schwartz information criterion. The gamma model did not converge for the males, but it did for the females, but it was the Weibull model that provided the best possible fit according to these criteria, as can be seen in Tables 37 and 38 below. For this reason, we discuss the Weibull regression model next.

Table 37 Schwartz information criteria for male AFT models

Comparison by Schwartz Criterion	
	sc
exponential	445.6403
weibull	329.8542
lognormal	350.2855
loglogistic	334.5996

Table 38 Schwartz information criteria for female AFT models

Comparison by Schwartz Criterion	
	sc
expential	508.7954
weibull	352.1067
lognormal	382.0904
loglogistic	364.7076
gamma	357.3177

#### 4.16.1 Weibull regression models

An accelerated failure-time model (AFT) is a parametric event history model that has the basic form:

$$\ln(t_j) = a + b_j \sum_{j=1}^J x_{t_j} + \ln(\tau_j) \quad (25)$$

where  $t_j$  = time till some event of interest takes place,

$b_j$  = a parameter coefficient estimate,

$x_j$  = a parameter, and

$\tau_j$  = an error term representing a particular distribution.

The reason that this model is called an accelerated model is that a unit increase in  $x_j$  increases the time to the event by  $\exp(\ln(1) + b) = 1.b$ . If  $b = .8$

and there were a unit increase in  $x$  then the time till the event would increase by  $\exp(\ln(1) + 2.2255) = 3.226$ . Because of the nature of the relationship between time and the covariate the effect of time is called accelerated [4, 240-241].

The exponential AFT model is often used as a baseline comparison for other AFT models. It is well suited for situations in which the hazard rate is constant over time.

$$\ln(t_j) = a + b_j \sum_{j=1}^J x_{t_j} + \ln(\tau_j) \quad (26)$$

where  $\tau_t \sim \exp(a)$  – that is, the error is distributed “as an exponential with a mean of  $\exp(a)$  [4, 254-255].”

#### 4.16.2 Weibull regression models

The Weibull regression model is more appropriate when the hazard rate is consistently increasing or decreasing over time. This model has two parameterizations. We will begin formulating the model in the proportional hazards metric and then show how to convert its parameters to the accelerated failure time metric. First, the Weibull regression model can be parameterized in the proportional hazards metric as

$$\ln(t_j) \sim Weibull(a, p) \quad (27)$$

where a Weibull distribution is a Gumbel extreme value distribution with a shape parameter,  $p$ , such that the scale (dispersion) parameter,  $\sigma = \frac{1}{p}$ .

The Weibull survival function is specified as

$$S(t) = \exp(-\lambda_j t^p) \quad (28)$$

where  $\lambda_j = \exp(X_j B)$ ,  $t$  = time till the event of interest,  $p$  = shape parameter, and  $X_j B$  = the parameter vector.

The Weibull hazard function is defined as

$$h(t) = p\lambda_j t^{p-1} \quad (29)$$

where  $\lambda_j = \exp(X_j B)$ ,  $t$  = time till the event of interest,  $p$  = shape parameter, and  $X_j B$  = the parameter vector.

However, the Weibull regression model is usually expressed in the accelerated failure time metric as

$$\ln(t) = a + X'_j B + \ln(\tau_j) \quad (30)$$

where  $\tau_j = \frac{\Gamma'(1)}{p}$ ,  $t$  = time till the event of interest,  $\ln(\tau_j)$  follows a Gumbel extreme value distribution with  $p$  = shape parameter, and  $\Gamma'(1) = \text{digamma}(1)$ ,

which is the negative of the Euler's constant,  $\approx -0.5722157$ . In this metric, the acceleration factor is  $\lambda_j = \exp(X_j' B)$ . In the proportional hazards parameterization, the effect of the covariates is to accelerate time by this factor to explain hazard rate (the time till the event), as compared to the baseline model in which all of the covariates would be equal to zero.

The implications for functional form are threefold: When  $p=1$ , the model reduces to an exponential model with a constant hazard rate; when  $p > 1$ , the hazard rate monotonically increases; and when  $p < 1$ , the hazard rate monotonically decreases.

The coefficients can be converted from one parameterization to the other by using the equality,

$$\beta_{aft} = \frac{-\beta_{ph}}{p} \quad (31)$$

where  $\beta_{aft}$  = the parameter in the accelerated failure time metric,  $\beta_{ph}$  = the parameter in the proportional hazards metric, and  $p$  = the shape parameter[4, 256-266].

How do we interpret the parameter estimates in Tables 39 and 40? How does time get accelerated? Table 39 reveals the parameters of the male Weibull regression model. The shape parameter,  $p$ , of this model is larger than one, so the hazard rate for the model is monotonically increasing. This observation is consistent with the forms of the hazard and cumulative hazard functions that we have plotted, and hence, the superior fit of this model compared to that of the others.

Equation 30 explains the relationship between parameters of the Cox and the AFT model. The Cox model parameter estimate and the accelerated failure time (AFT) model parameter, estimate have opposite signs. We naturally log the parameter estimates in the AFT model to antilog the exponentiation of the parameters. When we exponentiate time, based on  $e = 2.718...$ , we accelerate a process. If time is positive, there is acceleration. If time is negative and in the exponent, we decelerate the process.

The minus sign in the exponent merely refers to an exponential decline in decay rate parameter, as if we were computing the half-life or decay rate of a radio-isotope. A decline in this decay rate is a deceleration, whereas an increase in the velocity is an acceleration of the process. Hence the notion of accelerated time. When the effects of the covariates are incorporated, positive signs accelerate the time contraction with respect to the onset of the event of interest. If  $\lambda = \exp(X_j' B)$  represents the parameter vector in equations 27 and 28, exponentiation magnifies the effect after that vector is multiplied by  $t^p$  to obtain the survival rate. In the hazard rate, the parameter vector,  $\lambda_j$  gets multiplied by  $t^{p-1}$ , and the the time component of the hazard rate is exponentiated and accelerated, as long as the shape parameter exceeds one. If the shape parameter is less than one, deceleration of the covariates occur.

To construct the formula for this model from the Table 39, we would decide whether we were going to specify the survival or the hazard rate. Suppose we

chose the survival function. Cleves et al. specify the baseline survival function as [4, 265]

$$S_0(t_j) = \exp[-\{\exp(-\beta_0)t_j\}^p] \quad (32)$$

They furthermore maintain that the survival function, conditional upon the covariates, can be expressed as [4, 265]

$$\begin{aligned} S(t_j|x_j) &= S_0 \exp\{-X_j B_x t_j\} \\ &= \exp - \{\exp(-\beta_0) \exp(-X_j B_x) t_j\}^p \\ &= \exp - \{\exp(-\beta_0 - X_j B_x) t_j\}^p \end{aligned} \quad (33)$$

If we were formulating the model on the basis of the hazard function, we would commence by estimating the baseline hazard function.

$$h(0) = pt^{p-1} \exp(a) \quad (34)$$

where  $a$  = the constant of the model and  $p$  = the shape parameter, which is estimated and presented at the bottom of Tables 39 and 40, when we run the analysis with the nohr option.

#### 4.16.3 Male Weibull AFT regression model

In Table 39, we find a similar model to that displayed in Table 34, except that the signs are not the same. In Table 39, it can be seen that we have collapsed age into three groups to better observe the potential heterogeneity in the Weibull model. The junior (youngest) category is being used as the reference group, so that has been removed from this model. The signs of the coefficients of the retained parameters have been reversed (due to the conversion from the proportional hazards parameterization to the accelerated failure time metric. Almost all of the variables that were significant in the omnibus Cox regression for male respondents are significant in this Weibull AFT regression model, with minor exception. Having a widowed status in wave one has become nonsignificant and can be eliminated. Partner support in 1986 was of quasi-significant status before and remains so now. This could be trimmed if we were using a 0.05 cut-off, which we are not. Economic problems during wave in recent wave three years were teetering on the cut-off point before, but now have just gone over that point, so they could be trimmed as well. Let us consider the meaning of the parameter estimates.

In both the Cox and Weibull regression models the geographic regions have coefficients that are similar in magnitude but opposite in sign. In Table 39, Taraschanskiy is negatively related to time till level 25 depression, perhaps because Tarashanskiy is far south of the areas where residents were exposed to substantial Cesium 137 deposits. However, Korotsenskiy was downwind of

substantial radioactive fallout. In the other areas, people were less exposed. Many people were resettled into Zhitomirskiy, which might account concern exhibited by residents of that area.

Other significant socioeconomic factors included having a job as a particular kind of laborer. Wave two was a time of economic turmoil right after the fall of the soviet union. For some reason factory, transportation, and cleaning work is negatively related to the time till onset. Holding a job at this time appears to be positively related to the length of time till onset of level 25 depression.

The major negative life events that were related in this model are those of divorces in wave two and catastrophes in wave three. Divorces in wave two were strongly relate and catastrophes in recent years seemed to attenuate the impact on the time till substantial depression.

Among the stresses and hassles positively related to the time till onset were those which stemmed from relationships in wave one and one's job during wave two. Although health and housing issues were found to be related, they seemed to have an inverse relationship with the time till onset.

Countering these adverse effects were buffers and supports. Partner support during in 1986 and Chornobyl support that same year were not quite so significant as they may have been. Their significance levels dropped into the quasi-realm between 0.05 and 0.10. Perhaps the buffers were wearing thin by the time of the interviews.

Nonetheless, self-assessed health reports relating to the respondent's mental health became significant in the second and third wave. But the nature of the relationship seems to have changed from one wave to the other. During wave two, there was an inverse relationship, but by wave three the relationship had become significantly positively linked to the time till onset of level 25 depression. This may be a reflection of a growing awareness of the increasing hazard to these respondents.

As for actual medical diagnoses, heart attacks were clearly inversely related to the time of onset of the substantial depression. Natural contraception was a health behavior that was significantly positively related to the delay in onset of that depression in men.

In both models, PTSD emerges as a highly significant explanatory variable with respect to the time till the first onset of depression for men. The inverse relationship between the amount of PTSD and the length of time till onset indicates that the more the PTSD, the shorter the time till onset. This is an important and interesting finding that is found regardless of whether a semi-parametric method or a parametric method is applied for the analysis. The advantage of the parametric analysis is that once the distribution is identified and known, more accurate estimates and forecasts can be generated with the parametric model regarding the mean or median time till the event or event the hazard or cumulative hazard rate for the respondents.

Most of the remaining explanatory variables relate to general situational risk awareness or general radiation awareness. Table 39 reveals that concern about nutritional problems seems to have been inversely related to the time till onset, whereas trust in governmental reports about Chornobyl seems to



be positively related to the time till onset, while concern about contemporary economic problems seems to have largely faded from significance these days.

Table 39 Male Weibull AFT regression model

Weibull regression -- accelerated failure-time form

No. of subjects	=	138	Number of obs	=	138
No. of failures	=	136			
Time at risk	=	1871			
Log pseudolikelihood	=	-93.898227	Wald chi2(20)	=	2260.46
			Prob > chi2	=	0.0000

(Std. Err. adjusted for 138 clusters in id)

_t	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Korostenskiy	-3.17356	.2166919	-14.65	0.000	-3.598268	-2.748852
Narodichev-y	-1.215731	.2867179	-4.24	0.000	-1.777688	-.6537743
Radomische-y	-.9009331	.221497	-4.07	0.000	-1.335059	-.4668069
Tarascheskiy	.8409987	.1408393	5.97	0.000	.5649588	1.117039
Zhitomirskiy	-.3504347	.1003906	-3.49	0.000	-.5471966	-.1536728
_Iagegrp3_2	-.2071715	.1141079	-1.82	0.069	-.4308188	.0164759
_Iagegrp3_3	-.2513432	.1449232	-1.73	0.083	-.5353874	.032701
mar5w1	.1923914	.1451708	1.33	0.185	-.092138	.4769209
occ5w3	.6114913	.1275284	4.79	0.000	.3615403	.8614423
dvcew2	-.6366733	.2363822	-2.69	0.007	-1.099974	-.1733726
cataw3	2.126682	.2810774	7.57	0.000	1.575781	2.677584
shfamw1	.003844	.0012799	3.00	0.003	.0013353	.0063526
shrelaw1	-.006487	.0017279	-3.75	0.000	-.0098735	-.0031005
shjobw2	-.0034972	.0014052	-2.49	0.013	-.0062514	-.000743
shhlw2	.0054587	.0013906	3.93	0.000	.0027331	.0081842
shhousw3	.0037509	.0016953	2.21	0.027	.0004281	.0070736
suchrw1	.0059198	.003673	1.61	0.107	-.0012792	.0131188
mhlthw2	.012213	.0017879	6.83	0.000	.0087087	.0157173
mhlthw3	-.0083313	.0020259	-4.11	0.000	-.0123021	-.0043605
icdx3nr6	2.474383	.2170497	11.40	0.000	2.048973	2.899792
ncontw1	-.2495329	.1005855	-2.48	0.013	-.446677	-.0523889
MiPTSD	-.0266719	.0034345	-7.77	0.000	-.0334034	-.0199404
defnw1	.0043464	.0018357	2.37	0.018	.0007486	.0079443
defnw2	.0029555	.001288	2.29	0.022	.000431	.0054799
efradw3	-.0067045	.0015022	-4.46	0.000	-.0096486	-.0037603
trgovw1	-.0056413	.0011851	-4.76	0.000	-.0079641	-.0033185
_cons	4.030417	.337542	11.94	0.000	3.368847	4.691987
/ln_p	.9208884	.0751875	12.25	0.000	.7735237	1.068253
p	2.511521	.188835			2.16739	2.910291
1/p	.3981651	.029937			.3436082	.4613844

#### 4.16.4 Female Weibull AFT regression model

The female Weibull regression model also provides us with an improvement of fit over the competing AFT models. Table 40 displays the parameters of this model for our convenience. We have examined variation according to age group

and have discovered some heterogeneity. We have reason to believe that the seniors are more unstable and vulnerable than the juniors. Therefore, we use cluster robust standard errors to control for this shared frailty.

Table 40 Female Weibull AFT regression model

Weibull regression -- accelerated failure-time form						
No. of subjects	=	186		Number of obs	=	186
No. of failures	=	182				
Time at risk	=	2360				
				Wald chi2(18)	=	66512.21
Log pseudolikelihood	=	-126.19436		Prob > chi2	=	0.0000
(Std. Err. adjusted for 186 clusters in id)						
_t	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Irpenskiy	.5833975	.2230778	2.62	0.009	.146173	1.020622
Kyivskiy	.2035143	.0727423	2.80	0.005	.0609421	.3460866
_Iagegrp3_2	-.0337577	.0785768	-0.43	0.667	-.1877654	.1202501
_Iagegrp3_3	-.2001909	.0813837	-2.46	0.014	-.3597001	-.0406817
mar2w1	-1.053826	.0939155	-11.22	0.000	-1.237897	-.8697548
occ5w1	1.468141	.1993835	7.36	0.000	1.077357	1.858926
occ4w2	.3266465	.1002593	3.26	0.001	.1301419	.5231511
occ5w2	-1.333018	.1213112	-10.99	0.000	-1.570784	-1.095252
deaw1	-.1907277	.0752972	-2.53	0.011	-.3383075	-.0431479
cataw1	-.4791425	.0797214	-6.01	0.000	-.6353936	-.3228914
phlthw3	.0014405	.0019803	0.73	0.467	-.0024407	.0053218
icdx3nr9	-1.553722	.2470302	-6.29	0.000	-2.037892	-1.069551
icdx4nr7	-2.265153	.1699094	-13.33	0.000	-2.598169	-1.932137
icdx4nr9	-2.495561	.1593276	-15.66	0.000	-2.807837	-2.183284
icdx5nr2	-2.19544	.2055207	-10.68	0.000	-2.598253	-1.792627
icdx5nr11	1.262625	.0984325	12.83	0.000	1.069701	1.455555
injothr	-.1805663	.0940894	-1.92	0.055	-.3649783	.0038456
contw2	-.2772753	.0745885	-3.72	0.000	-.4234659	-.1310846
WHPer	.0061779	.0021282	2.90	0.004	.0020066	.0103492
BSIoc	-.0377422	.0083931	-4.50	0.000	-.0541924	-.0212921
BSIanx	-.0407523	.0107815	-3.78	0.000	-.0618836	-.019621
HP2work	.1987319	.078451	2.53	0.011	.0449709	.352493
neiwl	-.0020802	.0009857	-2.11	0.035	-.0040121	-.0001483
toxic	.0025759	.000946	2.72	0.006	.0007218	.00443
_cons	3.762048	.2784678	13.51	0.000	3.216261	4.307835
/ln_p	.9199819	.0584583	15.74	0.000	.8054057	1.034558
p	2.509245	.1466863			2.237604	2.813863
1/p	.3985262	.0232972			.3553834	.4469066

What is new and interesting about this model is that it reveals a different pair of areas that were significant—namely Irpenskiy and Kievskiy. With respect to socio- demographic factors, it reveals that cohabiting in 1986 is significantly related to the time till first onset of level 25 depression. Having work as in a factory, transportation, and cleaning, in 1986 and the following decade caused a sign reversal in the impact on time till onset from a positive sign in 1986 to a deceleration in the following decade. Being a skilled craftsman in wave two was

inversely related to the time of onset in this respect.

As for major negative life events, the women were more influenced by deaths and catastrophes in 1986. Somehow, those things were negatively related till the time of onset.

Self-reported good health in wave three faded in significance altogether in connection with the time till onset of depression.

Among the medical diagnosis received, there were stroke, which was negatively related; gastritis which was positively related; heart attack, which was negatively related; and perhaps one of the most curious is that of thyrotoxicosis, which was significantly negatively related to the time of onset. Also peripheral-vascular and rheumatological ailments were among the diagnoses issued.

With respect to health behaviors, we note that the use of contraception is negatively related to the time of onset.

The health scales were able to identify anxiety, obsessive-compulsiveness, and emotional reaction as some of the traits that plagued people. The impact on work was negatively related to the time till depression.

The female respondents moreover had depended on their neighbors in 1986 and believed that radioactive materials could remain toxic for thousands of years and were concerned that they may have injured someone else during 1986. In sum, these were the risk factors related to depression as indicated by the Weibull regression for the female respondents.

#### 4.16.5 Model fitting

One of the advantages of longitudinal research is that we can examine the shape of the impact over time. We can fit the baseline hazard and graph it for both males and females. We overlay the effect of the covariates to accelerate the failure time. We compare the difference between the two functions on a lowess overlay plot to ascertain what kind of acceleration or deceleration the covariates had on the baseline function, as shown in Figures 11 and 12. In the plot for the males, we notice three salient outliers, represented by spikes of hazard, in red on the part of the model with the covariates included. The smallest spike occurs 1986, which we might suspect as the impact of Chornobyl. The second largest spike takes place at about 1993 to 1994, which might represent the Ukrainian independence, and the third largest spike seems to take place around 17-18 years after 1980, which might indicate Russian default on their debt in 1998. What was happening in the Ukraine at that time is a matter for further exploration at this juncture.

In the graph for the females, we take note of the change in scale of the depression. In the male graph, the vertical axis extended from 0 to 1000, whereas in the female graph the vertical axis extends from 0 to almost 400. Whereas in the male graph observed three sudden spikes or hazard outliers. In the female graph we see a different pattern over time: Three sudden increases of a smaller magnitude with linear declines in 1981-1982, 1996, and 2003-2004. What was taking place in the Ukraine at those times among the women remains a matter for further exploration also.

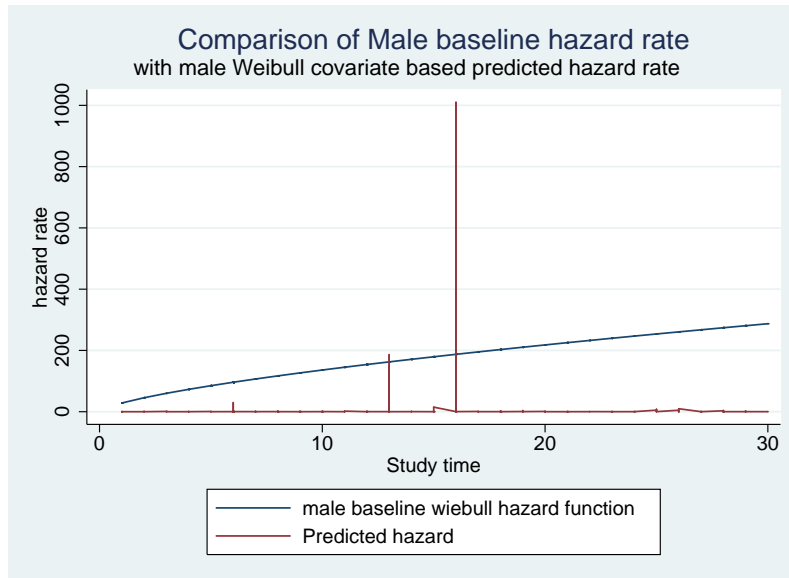


Figure 11: Comparing the baseline hazard with the covariate impacted hazard rate for males

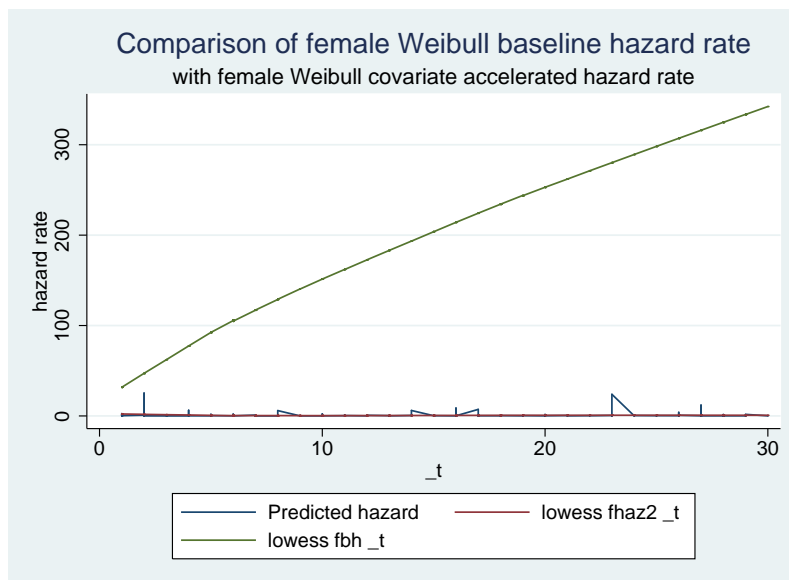


Figure 12: Comparing the baseline hazard with the covariate impacted hazard rate for females

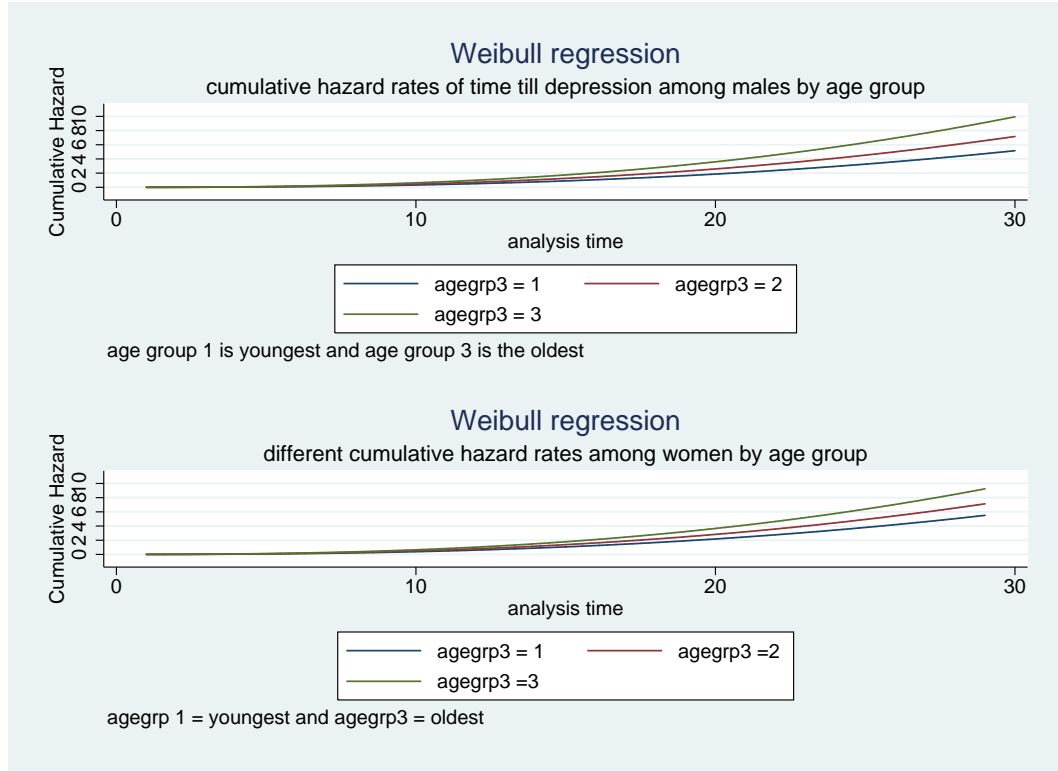


Figure 13: Graphing significant heterogeneity of the cumulative hazard by gender and age group

When we test these differences for statistically significant. A Wilcoxon (Breslow) test reveals that the males exhibit a significant time dilation from 2.36 to 2.44 from the baseline to the male covariate model of the natural log of the median survival time ( $\chi^2(273) = 818.01, Pr > \chi^2 = 0.000$ ), whereas for the females there is a significant dilation of the the natural log of the median survival time from a baseline of 2.467 to a covariate adjusted full model impact of 2.506 ( $\chi^2(337) = 1029.87, Pr > \chi^2 = 0.000$ ).

There was significant but miniscule heterogeneity in the Weibull models, as can be seen in Figure 13. When we attempted to model them as shared or unshared frailty, the amount was so small that parsimony required that we drop this out of the model. As mentioned before, for both males and females, the Weibull model provided the optimal fit for a monotonically rising hazard rate.

#### 4.16.6 Goodness of fit

Before forecasting, we want to validate the goodness of fit of these male and female accelerated failure time models. Patrick Royston (MRC clinical trials

unit) has written to compute an adjusted  $R^2$  for accelerated failure time models using a program, str2ph.ado, We applied this program to discover an adjusted  $R^2$  for the two models and the results are show in Table 41.

Table 41 R square and adjusted R square of AFT models				
R <sup>2</sup> (explained variation): Weibull regression models				
Gender	Obs	Events	Adj. R <sup>2</sup>	R <sup>2</sup>
male	9514	136	0.3225	0.4066
female	11328	182	0.3496	0.4089

#### 4.16.7 Forecasting

We can estimate a baseline hazard, such as a time till an event. The baseline hazard is the time to the event of interest, when all covariates are equal to zero, based on the constant or average. Then we can load the covariates in and compare the acceleration of the time to that provided by the baseline hazard. We can do the same thing with the survivorship function. Because we can run the baseline model with all covariates equal to zero, and generate the baseline survival function in a Weibull regression model. We can then enter the covariates and regenerate the survival function, after which we can plot them on an overlay graph for purposes of comparison.

The baseline survival function for the Weibull regression model can be based on

$$S(t) = \exp(-\exp(a)t^p) \quad (35)$$

Table 41 Generating the baseline survival function from a male Weibull model

```
. xi:streg gender, nohr dist(weibull) iterate(20) time vce(cluster id) nolog
Weibull regression -- accelerated failure-time form
No. of subjects      =          340          Number of obs   =          340
No. of failures      =          334
Time at risk         =          4340
Log pseudolikelihood =    -363.49525
Wald chi2(1)         =          0.10
Prob > chi2           =          0.7487
(Std. Err. adjusted for 340 clusters in id)
```

_t	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
gender	-.0211044	.0658906	-0.32	0.749	-.1502475	.1080387
_cons	2.702288	.1091495	24.76	0.000	2.488359	2.916217
/ln_p	.5089591	.0336914	15.11	0.000	.4429252	.574993
p	1.663559	.0560476			1.557256	1.777118
1/p	.601121	.0202526			.5627088	.6421552

so we examine the output for the males and find that the constant = 2.702 and the shape parameter= 1.664.

$$S(t) = \exp(-\exp(2.702)t^{(1.664)}) \quad (36)$$

We can proceed to graph this baseline survival curve, add the covariates, and then regenerate the survival function, and then plot the two curves on the same graph to compare the covariates effect on the time to the event, or we may use the formula for the baseline hazard rate in equation 33 and then graph the baseline against the covariate controlled hazard rate to show the acceleration effect of the covariates on the hazard rate, as illustrated for females in Figure 12.

Other graphs displaying this kind of effect are those in Figures 9 and 10, displaying the differential effects of residing in raions far from or close to the accident site. Alternatively, we might focus on the effect on survival time by graphing the natural logged functions of the median survival times for the baseline and for the full model, displaying them in Figure 14.

To test whether the covariate acceleration or deceleration was significant, we can estimate the natural log of the median time to the event without the covariates, add the covariates, re-estimate the natural log of the median time to the event, and perform a log-rank or Wilcoxon test for equality of the summed ranks between the two distributions to ascertain whether there is a significant difference between them.

Once we know the distribution, the parametric models, if we can fit them, can provide more accurate estimates of the accelerated failure time than semi-parametric models, which essentially ignore the baseline hazard. We can do this within the sample, if we are testing hypotheses, or we can perform this forecast

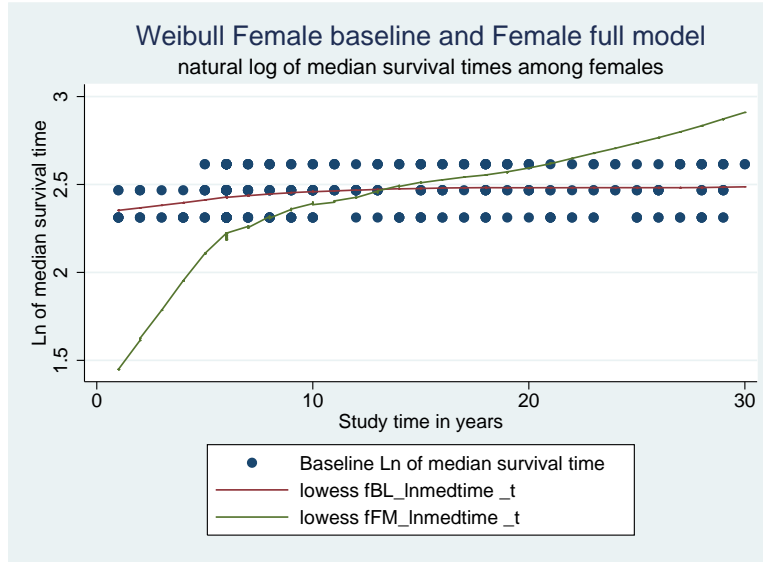


Figure 14: Female baseline compared to full model effects

beyond the estimation sample, if we are interested in prediction of the general or individual hazard. Especially interesting is the counter-factual capability to set the values of the variables to whatever the researcher may wish to test, and to see the effect of such counterfactual situations on the forecasts. This "What if" capability endows the researcher with considerable power in scenario forecasting if the variables are strongly exogenous, and policy planning given pre-defined contingencies provided that the variables are superexogenous.

#### 4.17 The multi-episode model: Directions of further research

When we commence our model building, we confront a situation with repeatable events. In the multi-episode model, there are multiple transitions from one state to another. Each episode of a repeatable event is called a spell [22, 46]. We could model each episode as a separate transition. We need a covariate for the time since the last transition and another covariate indicating the number of the previous spell. By knowing the nature of the previous state, we know the direction of the transition under analysis.

One approach is to analyze each spell separately as a single transition. We first build a model to explain the rate of the first transition. Then we build a model to explain the second transition, and so on. The models may differ from one transition to another. Separately, they will explain the different transitions from the starting point to each relapse or onset of level 25 depression.

As we proceed to analyze later episodes, we may see that fewer respondents



report so many relapses. Our sample size may dwindle as the number of relapses increases. We may reach a point that so few respondents report a transition, that the sample size will be insufficiently large to use asymptotic statistical methods for our analysis. To avoid the pitfalls of micronumerosity, we have to cut-off the analysis after four spells.

As we analyze the specific transitions, we may wish to compare the change in the parameters from one model to another. This will help indicate how the parameters explain different transitions and how those transitions differ from one another.

In the analysis of a multi-episode model, we could use duration dependence as a covariate in a model of repeated depression spells. We could model these spells in stages. The first stage could be a model of the first transition. The second stage could be a model of the second transition. We could proceed to the third and fourth stages accordingly.

In each of these stages, the number of times a relapse has occurred could be a covariate, in accordance with the semi-Markov model assumptions of a Markov renewal model [5, 240-251], [19, 95]. Both Cox regression and complementary log-log models have been used to perform this kind of relapse analysis during the time since the last screening, where a dummy variable is coded as zero to indicate no recurrence and one to indicate recurrence since that time [5, 241].

Each stage could generate a model and finally, the parameter estimates could be comparatively analyzed for change from stage to stage. To be sure of applying a test for retention, with equal statistical power, all parameter estimates in the final modeling should undergo the Hendry-Richard general-to-specific model and variable selection protocol. The end result would be a model for each transition and a comparison of parameters in the models [2, 109-115].

Another approach would be to use the natural log of the number of years of depression as a dependent variable in a multi-episode model with duration and age dependence as covariates in the model.

We will address the relapses of the respondents in the next paper on multiple episode models of depression.

#### 4.17.1 Assumptions

We assume that the spells are conditionally independent of one another, with the same baseline hazard rate. Thus, the covariates can account for previous spells and their durations.

The proportionality of hazards assumption postulates that the change in the hazard is a proportional one throughout the estimation process. This assumption may be tested with the interaction of the covariate and time. If the interaction is statistically significant, the assumption is violated. If the interaction is not statistically significant, the assumption is fulfilled. By comparing the results of the two models we can get a sense of what the parameter instability is and what the range of effects are.

As for the accelerated failure time metric, we can formulate a baseline hazard, and then compare this to the full model when we forecast the time or  $\ln(\text{time})$

till the episode in question. We will perform this task for the subsequent three episodes on the part of males and females who relapse.

The assumptions of linearity and additivity can only be tested by running models with interactions among the covariates. If we test for functional form by graphing the martingale residuals against If these interactions are not statistically significant, the additivity assumption is fulfilled.

We use the Breslow correction for ties for the Cox repeated episode models. We take the final model discovered by the modeling process for the Cox regression model and use a general-to-specific approach for pruning the model of its irrelevant parameters.

We will address the relapses of the respondents in the next paper on multiple episode models of depression.

## References

- [1] BBC Ukraine Timeline accessed 27 February 2012 BBC world wide web site <http://news.bbc.co.uk/2/hi/europe/1107869.stm>
- [2] Blossfeld, H.-P., Golsch K., Rohwer, G. 2007 Event History Analysis with Stata Mahwah, NJ: Psychology Press, 17, 85, 86, 120-121, 183, 233-235.
- [3] Blossfeld, H.-P., Hammerle, A, Mayer, K. U. 1989 Event History Analysis: Statistical Theory and Application in the Social Sciences Hillsdale, NJ: Lawrence Earlbaum Associates, 60-74.
- [4] Cleves, M., Gould, W., Gutierrez, R.G., and Marchenko, Y.V. 2010 An Introduction to Survival Analysis using Stata College Station, Tx: Stata Press, 7, 129-131.
- [5] Collett, D. 1994 Modeling Survival Data in Medical Research London, UK: Chapman Hall, 238-251.
- [6] Engle, R.F., Hendry, D.F., and Richard, J.F. 1983 Exogeneity Econometrica, 51, 277-304.
- [7] Harrell Jr., F.E. 2002 Regression Modeling Strategies New York, NY: Springer, 58-85, 358, 476-493.
- [8] Hendry, D.F. and Richard, J.-F. 1982 On the formulation of dynamical models in empirical econometrics Journal of Econometrics, 20, 3-33.
- [9] Kalbfleish, J.D. and Prentice, R.L. 1980 The Statistical Analysis of Failure Time Data New York, NY: John Wiley and Sons, Inc., 40-41, 190, 198.
- [10] Lee, E.T. 1992 Statistical Methods for Survival Data Analysis 2nd.ed. New York, NY: John Wiley and Sons, Inc., 10.

- [11] Mausner, J.S., Bahn, Kramer, S. 1985 Epidemiology-An Introductory Text 2nd ed. Philadelphia, PA: J. B. Saunders and Co., 44.
- [12] Miller, Jr., Rupert G. 1981 Survival Analysis New York, NY: John Wiley and Sons, Inc., 2,5,6.
- [13] Rabe-Hesketh, S. and Skondal, A. 2008 Multilevel and Longitudinal Modeling using Stata 2nd ed. College Station, Tx: Stata Press, 331-372.
- [14] Royston, P. and Lambert, P.C. Flexible Parametric Survival Analysis using Stata: Beyond the Cox Model College Station, TX: Stata Press, 131-140.
- [15] Royston, P. and Sauerbai, W. 2004 A new measure for prognostic separation in survival data. *Statistics in Medicine*, **23**, 723-748.
- [16] Russia Timeline 1988-1995 [http://timelines.ws/countries/RUS\\_D\\_1988\\_1995.HTML](http://timelines.ws/countries/RUS_D_1988_1995.HTML) accessed 25 February 2012
- [17] Selvin, Steve 1996 Statistical Analysis of Epidemiological Data New York, NY: Oxford University Press,
- [18] StataCorp. 2011 [ST] Survival analysis and epidemiological tables Release 12 College Station, TX:Stata Press, 415.
- [19] Tuma, N.B. and Hannan, M.T. 1984 Social Dynamics: Models and Methods San Diego, CA: Academic Press, 82-83, 92-94, 187-264.
- [20] State Department Ukrainian history background notes accessed 27 February 2012 Department of State, United States Government, web site. <http://www.state.gov/r/pa/ei/bgn/3211.htm#history>
- [21] Time Line Ukraine accessed 27 February 2012 World Wide Web <http://timelines.ws/countries/UKRAINE.HTML>
- [22] Yamaguchi, K. 1991 Event History Analysis Newberry Park, CA: Sage Publications, 15-41, 46.