Comparative Forecast Evaluation of Post-Chernobyl Psychosocial Sequelae

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1. Introduction

On April 26, 2019, a hydrogen explosion at the Chernobyl nuclear plant in Ukraine. occurred after a core meltdown following a failure of the cooling system. The catastrophic meltdown at the Chernobyl nuclear power plant was the most severe nuclear accident in the history of the nuclear power industry to date.

Subsequent fires gave off radioactive isotopes for the next 10 days, consisting of Cesium 137 (^{137}Cs) and Iodine 131 (^{131}I), among other particulate matter. Changing weather patterns widely dispersed the contamination across Ukraine, Belarus, the Russian federation, and much of Europe, displayed as the darker areas in the yellow maps of figures 1 and 2.[1,2] Protracted exposure to radioactive fallout exposed the population to the threat of physical and psychosocial risk.

Figure 1: ^{137}Cs deposits in Ukraine after Chornobyl disaster.[1]

Figure 2: ^{137}CS deposits in Europe and the Russian Federation after accident.[2]

a) Psycho-Social responses of Anxiety, Depression, and Civilian PTSD among Ukrainians

Early studies were epidemiological case control studies, focusing on highly exposed groups of persons.[16,18] We study the general population with longitudinal methods capable of overcoming critical drawbacks of observational studies.[16,18]

In the 25th anniversary of Chernobyl, a scientific forum reported that the principal public health effects were psychological[2,3,18]. Anxiety, depression, and civilian PTSD self-reports were collected in a representative survey conducted among 702 residents in Kiev and Zhytomyr oblasts from 2009-2012. From Figures 3, we see that anxiety and depression, co-moved and were highly inter-correlated ($r > 0.9$, $\alpha > .7$),[11] representing their historical comorbidity. By averaging depression and anxiety levels , we computed an indicator of psychosocial **distress.** We treated **civilian PTSD** as a separate indicator and conducted the first structural time series analysis of the sequelae of this disaster to examine external impacts.

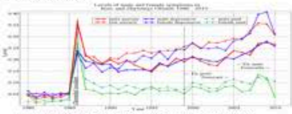

Figure 3: Male and Female reports of anxiety, depression, and civilian PTSD

With the time series overlay plot (Figure 3), we found other increases of distress over time, apparently enhanced by external events. Our review of Ukrainian history revealed percolation of gas price disputes that erupted in 2006 and 2009 with Russia cutting off the flow of natural gas (LNG) to Ukraine. Russia had been regulating the gas and oil supplies to manipulate the energy prices to coerce former Soviet States from becoming too politically independent and joining the NATO (Table 1). Ukraine as a transit hub of gas to Europe was critical to this coercive energy control (Figure 4). Cooperative former border states received discounted prices, whereas others had to pay higher prices.[6,7,10,35]

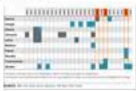

Table 1: Dates from 1990-2015 when Russia manipulated gas and oil prices for political reasons.[6,7]

Figure 4: Gas pipelines running through Ukraine.[6,8]

To preclude those impacts from doing so, we terminated our estimation at 2006. Hence, to assess the impact from Chernobyl our estimation had to circumvent confounding from external impacts, generally overlooked by earlier studies. Hence, we ceased to estimate our model at the end of 2005 and perform a scenario forecast over the 2006 to 2010 horizon to estimate what might have been the levels had no external change impacted Ukraine, like the Great Depression which coincided with Russia's 3 week gas cut-off in 2009, which closed 80% of the Ukrainian industrial sector.[6,8,35]

2. Hypotheses

1) The external dose of ^{137}Cs radiation will not significantly predict distress or PTSD among either males or females, (based on estimates of the 2008 United Nations Scientific Committee Report on the Effects.[19])
2) The perceived risk of exposure to the effects of radiation will be a primary driver of the distress and PTSD responses.
3) The BHG entanglement hypothesis will not prove consistent with our empirical findings[4]. If the BHG hypothesis is not consistent with our data, we do not have to shorten our data series to control or model it with a level-shift indicator.[4]
4) Gas cut-offs in 2006 and 2009 are entangled with incidence of distress and PTSD reported by our respondents.[6,8] Using data from 1980 through 2005 to build and estimate the model avoids confounding with the impacts of these events.
5) Multivariate state space models will be more accurate than the LASSO-VAR models (Yaffee et al., 2014).

3. AutoMetrics test of Bromet, Havenaar, & Guey entanglement hypothesis

Table 2: IS-SIS saturation does not select SI: 1991 as level-shift with Distress as the dependent variable.

[illegible]

Table 3: IS-SIS saturation does not select SI:1991 as a level-shift with PTSD as the dependent variable.

[illegible]

The implication is that there is no need to include a USSR collapse level-shift to model an increase of these sequelae. Nor need we end estimation earlier than we do to avert confounding of our endogenous series.[5,36]

4. Forecasting Models

a) Multivariate state space models

Because the depression and anxiety scores were highly correlated, and that the civilian PTSD score was highly correlated with the Distress score, we modelled by a multivariate state space model with a common local level. The model uses a diffuse prior to estimate the measurement and transition equations that form part of the model. This model could be applied to both the males and females separately, which is customary in the socio-medical analysis. The model is estimated by an Augmented Kalman filter and smoother by optimizing the log likelihood of the model. Structural break and outlier detection is incorporated into the modeling process using **STAMP 8.3 in OxMetrics 7.2.™**

The transition equation: $\alpha_{i,t+1} = d_t + T_t\alpha_{it} + H_t\eta_t$ where $\alpha_1 \sim N(a_1, P)$ (1)

where α_{it} = mx1 state vector containing unknown stochastic processes and unknown fixed effects." T_t = (mxm) transition coefficient matrix, H_t = (mxr) selection matrix of 0s and 1s, η_t = (Nx1) vector of errors, a_1 = random mean vector usually of mean zero and (mxm) variance P.[12,13]

The measurement equation: $y_{it} = c_t + Z_{it}\alpha_{it} + G_t\epsilon_{it}$ where $\epsilon_{it} \sim$ NID(0,I) (2)

where i = 1,…,N and t=1,…,n, y_{it} = a vector of observed indicators, c_t is a (Nx1) known constant vector, Z_{it} = factor loading matrix, α_{it} = state vector, and ϵ_{it} = (rx1) vector of measurement errors, y = (NX1) observation vector. (Ibid)

The state vector can be loaded with explanatory variables and structural break indicators to better fit the models.

The high correlation among the response variables allows for potential feedback.[34] When the covariance matrix among the latent components is not of full-rank, it is possible to make some of them dependent on others in the estimation and thereby allow for such interdependence in the Kalman filtering and signal extraction. The prediction is performed by the Kalman filter and signal extraction performed by disturbance smoothing. The model estimates are computed by maximum likelihood estimation of the likelihood function. Augmentation of the algorithm permits computation of nonstationary processes.[12,14]

4.b). Lasso-based variable selection for vector autoregression with exogenous variables

Robert Tibshirani developed the original LASSO algorithm in 1996.

a) *Original* least absolute shrinkage and selection operator (LASSO) in Equation 3.

$$\hat{\beta}^{lasso} = \text{argmin}[\beta_0, \beta_1, \ldots \beta_k]\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{k}\beta_j x_{ji})^2 \quad 3)$$

subject to $\sum_{j=1}^{k}|\beta_j| \le t$ where t is a tuning parameter chosen by cross-validation.[30]

b) *Adaptive* LASSO applies different weights to the model, as expressed in Equation 4.

$$\hat{\beta}^{adalasso} = \text{argmin}[\beta_0, \beta_1, \ldots \beta_k]\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{k}\beta_j x_{ji}) \quad (4)$$

subject to $\sum_{j=1}^{k}\omega_j|\beta_j| \le t$, where $\omega_j = |\hat{\beta}_j^{ridge}|^{-1}$.

c) *Weighted lagged adaptive* LASSO least absolute shrinkage and selection operator (WLadaLASSO) in Equation 5.[32]

$$\hat{\beta}^{WLadalasso} = \text{argmin}[\beta_0, \beta_1, \ldots \beta_k]\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{k}\beta_j x_{ji})^2 \text{ handles} \quad (5)$$

subject to $\sum_{j=1}^{k}\omega_j|\beta_j| \le t$, where $\omega_j = \left(|\hat{\beta}_j^{ridge}|e^{al}\right)^{-1}$, $a \ge 0$

and l = lag order (1 and 2) were tested.[33]

d) The 5-fold cross-validation was conducted owing to the 25-30 observation length.

5. Forecasts

a) Multivariate state space models

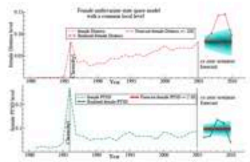

Figure 5: Female multivariate state space model with common local level

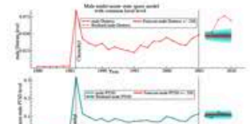

Figure 6: Male multivariate state space model with common local level

b) Multivariate state space parameter estimates

Table 4. Distress models

Females, $R_d^2 = 0.919$				
	Coefficient	RMSE	t-value	Prob
Chornobyl Incident	0.049	0.006	7.976	0.000
Level Break 1998	0.015	0.004	4.018	0.001
Perceived Risk	0.022	0.005	4.793	0.000
Males, $R_d^2 = 0.968$				
	Coefficient	RMSE	t-value	Prob
Chornobyl Incident	0.049	0.004	13.585	0.000
Level break 1996	0.009	0.002	4.698	0.000
Outlier 1997	-0.005	0.002	-2.549	0.020
Level break 1998	0.006	0.003	2.175	0.043
Level break 2004	0.012	0.003	3.554	0.002
Perceived risk	0.029	0.003	9.429	0.000

Table 5. PTSD models

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Perceived risk	0.029	0.003	9.429	0.000

c) Lasso-VAR model coefficients after shrinkage

Table 6 Distress response model coefficients

Gender	LASSO	Adaptive LASSO	WL LASSO, lag = 1	WL LASSO, lag = 2
Males	Workhealth (0.002) Homelife (0.006) Somatic (0.007)	Somatic (0.014)	Perceived Risk ([illegible])	Perceived Risk Lag 1 ([illegible])
Females	Workhealth (0.002) Social (0.003) Weekend (0.003) Somatic (0.016)	Social (0.007) Smoke (0.010) Somatic (0.016)	Perceived Risk ([illegible])	Perceived Risk Lag 1 ([illegible])

Table 7 PTSD response model coefficients

Gender	LASSO	Adaptive LASSO	WL LASSO, lag = 1	WL LASSO, lag = 2
Males	Weekend (0.003) Chernobyl (0.128)	Somatic (0.007) Weekend (0.006)	NA	NA
Females	Somatic (0.003) Doctor (0.020) Weekend (0.001) Planning (0.002) Chernobyl (0.124)	Weekend (0.018) Planning (0.012) Interests (-0.009)	NA	NA

6. Hypothesis test results

1) The reconstructed average male or female external dose was not selected as an explanatory variable in any of our models. This is consistent with expectations.
2) The perceived male and female risk of Chernobyl related health effects was found to be a significant primary explanatory variables in all state space models. It was only selected by the Distress Weighted Lagged Lasso algorithm with lags=1 and 2. This may reflect the inappropriate use of original and adaptive LASSO with time series data.
3) AutoMetrics with IS-SIS saturation did not retain a step-indicator (SI:1991) for any gender-specific model of Distress. Nor did it select a such a level-shift for the male or female AutoMetrics model of PTSD.. In support of this finding, the Lasso-based selection algorithms did not retain the 1991 level shift tested in either male and female models.[36] Hence, we found no overt empirical evidence for inextricable entanglement of general Distress or PTSD with the collapse of the U.S.S.R. in either of these different variable selection algorithms.
4) Russian gas cut-offs to Ukraine in 2006 and 2009 are reflected in a rise in Distress for women in 2006. For men, there is a delay of 12 months before their distress increases. For male PTSD, there is slight decline for a year before it PTSD begins to increase.[31]
5) All multivariate state space models selected the impact of Chernobyl, perceived health risks of Chernobyl-related exposure, and a positive level-shift in 1998 distress as significant explanatory variables as significant explanatory variable; they appear to be more consistent in variable selection than LASSO–based variable selection models.

7. Conclusions

Dot graphs that compare the ex post and ex ante forecasts are available on request. Our expectations from Hypothesis 1 that the reconstructed exposure was not significant is consistent with these findings. This variable was not retained by either algorithm as statistically significant.

Hypothesis 2 was consistent with the data for the state space models and with the WL LASSO with lags 1 and 2, and this is the version that should work best with time series.

After generated our *ex post* forecasts over a 1980-1997 forecast horizon, that became the training segment. However, our main objective was to obtain a scenario *ex ante* forecast evaluation over a 2005 through 2010 forecast horizon. Although (BHG) argued that the psychological effects of the Chornobyl disaster experienced by Ukrainians were inextricably entangled with the collapse of the U.S.S.R., we used two different algorithms of variable selection and retention to test this proposition with a step-indicator (SI:1991). Neither algorithm retained this variable, regardless of gender of the respondent. The direct implication is that we therefore did not have to include a U.S.S.R. collapse dummy indicator for our model to have been properly modeled. Nor did we have to truncate our estimation prior to 1991 in order to avoid confounding our endogenous variables with internal invalidity.

If, as BHG intimated, these psychological sequelae might be subclinical or latent; they should nonetheless be related to this 1991 step- indicator of the USSR collapse. Although their admonition might discourage some investigators to focus their attention on this area, this area might be a fertile ground for inquiry if external threats can be controlled for in a longitudinal analysis.

Hypothesis 4 is confirmed by the female data, exhibiting an increase in Distress in 2006. The male models exhibit a year delay in the same tendency of response.

Hypothesis 5 suggests that LASSO methods depend on a tuning parameter that is a function of the data size and magnitude. State space models appear to be more consistent in variable selection than

To evaluate the forecast accuracy, we use the mean absolute error (MAE) and the symmetric mean absolute percentage error (SMAPE). of the scenario forecast in Table 8. Had we used the mean square error variance, the possible existence of structural breaks—such as, outliers or level-shifts-- could inflate such error criteria. Also, the mean absolute percentage error is scale dependent. If the initial actual values are tiny, the percent error change is inflated by the small scale size. Although there are several versions of the SMAPE, we use the version in Equation 6. and the standard version of MAE in Equation 7, with a = actual, f=forecast, and T=total.

$$sMAPE = \sum_{t=1}^{T}\frac{200}{T}\left(\frac{|a-f|}{|a+f|}\right) \quad (6) \qquad MAE = \sum_{t=1}^{T}\frac{1}{T}|a-f| \quad (7)$$

According to the results listed in Table 8, the more accurate results for the criterion of choice is colored in red. The SMAPE criterion reveals that the State Space is more accurate in estimating the scenario forecast for PTSD, regardless of the gender. The MAE criterion mostly suggests the same conclusion. For the Distress models, the LASSO-VAR may be the more accurate of the two algorithms. When the State Space achieves more accurate estimates, it's forecasts are more often more accurate than those of the LASSO-VAR.

Table 8: SMAPE and MAE evaluations of the Scenario forecasts

[illegible]

References

1) DeCort et. al. (1998) "The Atlas of Caesium Deposition on Europe after the Chernobyl accident." Luxembourg: Office of the Official Publication of the European Communities, plates 19, 60.
2) Bromet, E.J., Havenaar, J.M. (2007). Psychological and perceived health effects of the Chernobyl disaster, *Health Physics*, **93**(5).
3) Bromet, E.J., Havenaar, J.M., and Guey, L.T. (2011) , "A 25 year retrospective review of the psychological consequences of the Chernobyl accident," Clinical Oncol. (R Coll. Radiol), 23(4), 297-305.
4) Bromet, E.J. (2012)"Mental health consequences of the Chernobyl accident", *Journal of Radiation Protection*. **32**(1).
5) Doornik, J.A.D. "Autometrics." in Castle, J. and Shephard, Neil (eds). [redacted] *Oxford, U.K.: Oxford University Press.*
6) Kinley III, D.(ed.) (2006). The Chernobyl Forum: 2003-2005, Chernobyl's legacy: Health, Environmental, and Socio-economic Impacts and Recommendations to the Governments of Belarus, the Russian Federation, and Ukraine, 2nd revised edition, Vienna, Au., *International Atomic Energy Association*, 10-20, 36-37.
7) Collins, G. (2018). "Issue Brief 7-18-17: Russia's use of the energy weapon in Europe," [redacted]
8) Connelly, H. et al. (2018). [redacted] New York: Rowman Littlefield, 4-14.
9) Campbell, D.T. and Stanley, J.C. (1963) [redacted] Chicago, Ill., 7-9.
10) The Economist (2006), "Russia turns off the gas taps." London: U.K. "http://www.economist.com/node/5327867."
11) Nunnally, J.C. (1978). [redacted], New York: McGraw-Hill, recommends a minimum alpha > 0.7 before combining items to form scales, 228.
12) Koopman, S.-J., Shephard, N.. Doornik, J.A.D. (2008) [redacted] London: Timberlake Consultants, Ltd., 40-42, 109-115,140-153.
13) Koopman, S.-J. and Durbin, J. (2001) [redacted] Oxford: Oxford University Press.
14) Harvey, A.C. (1989) [redacted] Cambridge: Cambridge University Press.
15) Commandeur, J.C. and Koopman, S-J. (2007). [redacted] Oxford: Oxford University Press.
16) Tarrell, , K.T. "Assessing bias in case-control studies: Proper Selection of case-controls.", *Stroke*, **22**(7) , 938-942.
17) Schuemie, M.J., Ryan, P.B., Doumichelle, W., Suchard, M.A., and Madigan, D. (2014). "Interpreting Observational studies: Why empirical calibration is necessary to correct p-values." *Statistics in Medicine*, 33, 209-218.
18) Balonov, MJ (2007): "The Chernobyl Forum: The Major Findings". *Journal of Environmental Radioactivity. IAEA.*, Vienna, Au., *6-12.*
19) Hendry, D.F. and Krolzig, H-M. (2001). The Automatic Econometric Model Selection using PcGETS 1.0. London: Timberlake Consultants, Ltd.
20) World Health Organization (2006). [redacted]
21) World Health Organization (2006). [redacted] http:[redacted] 93-97.
22) Bodner, L.(2016). "Backgrounder: Russia's Energy Disputes", *Council of Foreign Relations.* [redacted]
23) Parfit, T. (2006). "Russia turns off supplies to Ukraine in payment row, and EU feels the chill," *The Guardian* US edition, [redacted]
24) McFaul, M. (2018). [redacted] New York: Houghton Mifflin Harcourt., 68.
25) Sevastopol. *Wikipedia.* Russia was leasing the port of Sevastopol for their Black Sea fleet since Ukraine acquired independence. [redacted] 2018, Dec. 3 accessed.
26) Stegen, K. (2011). "Deconstructing the energy weapon: Russia's threat to Europe as a case study." *Energy Policy.* Elsevier Ltd., 6505-6512.
27) R Core Team (2018). R: A language and environment for statistical computing. R foundation for statistical computing. Vienna, Austria. [redacted]
28) StataCorp, (2009-2017). Stata 12 Reference Manual N-R, College Station, Tx., StataCorp, LP.
29) OxMetrics version 8. Timberlake Analytics, Ltd. London, U.K. Timberlake Analytics.
30) Tibshirani, R. (1996). Regression shrinkage and selection via the LASSO. *J. Royal Statistical Society, B, (58)1, 267-288.*
31) Yaffee, R.A., Nikolopoulos, K., Reilly, D.P., Crone, S.F., Wagoner, K.D., Douglass, R.D., Amman, B.R., Ksiazek, T.G., and Mills, J.M.(2011). [redacted] *Federal Forecasters Brown Bag Lunch,* George Washington University, *http://ww2.gwu.edu/~forcpgm/Yaffee.pdf:19.*
32) Zou, Hui (2006). The Adaptive Lasso and its Oracle Properties. *Journal of the American Statistical Association.*(**101**)476, *1418-1429.*
33) Konzen, E. and Ziegelmann, F.A.(2016). Types of penalties for covariate selection and forecasting in time series. *Journal of Forecasting.* **35**, *592-612.*
34) Luktepohl, H.(2005) [redacted] New York:Springer.
35) NATO Review magazine (2017). "Transatlantic energy security in the Ukrainian energy crisis: A blessing in disguise." Brussells, Belgium: NATO Review Magazine, [redacted]
36) Doornik, J.A.D. and Hendry, D.F.(2013) [redacted] Vol.5, London, U.K.:Timberlake Ltd, 38-52.

The 37 page paper and its reference list are available upon request.

See attached sheet for complete acknowledgments