A Comparative Forecast Evaluation of the trajectories of post-Chornobyl nuclear accident psycho-social sequelae

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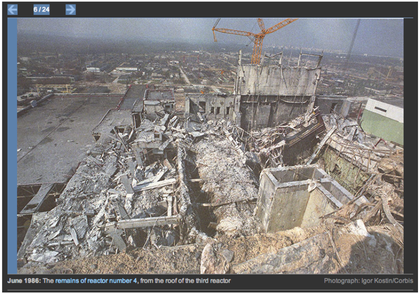
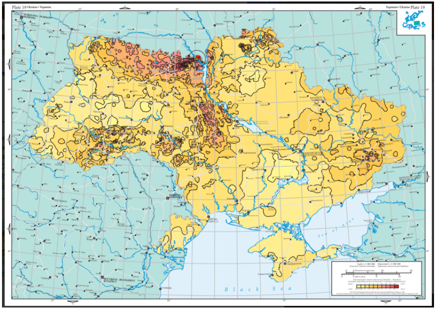
Historical background: Explosion of Reactor four & ^{137}Cesium contamination in Ukraine



Explosion at Reactor Four



Measured contamination within Ukraine

Literature Review

- Bromet, Havenaar, and Guey, (2011) (BHG) concluded that mental health effects were the most significant public health consequence [3].
- Bromet, (2012) (EB) argued that "The most common mental health consequences : depression, anxiety, post-traumatic stress disorder..., and stigma [4]"
- Havenaar et al. (1997) wrote that most psychological effects in the general public were driven by the perception of exposure [14] [37].
- BHG (2011): "a vast array of physical and psychosocial exposures ... are all but impossible to disentangle from the general turmoil that followed the collapse of the USSR in 1991. [3]"

Methodology in previous studies

- Cross-sectional
- Did not control for external impacts.
  - Failure to control for Russian energy dependency in 2006 and 2009
  - Putin tried to quadruple the natural gas price in 2006
  - Russia stopped gas flow to Ukraine in January of 2006.
  - Amidst the Great Recession, Russia cut-off gas for three weeks in Jan 2009, causing closure of approximately 80% of Ukrainian factories
- Failed to randomize respondent selection to obtain a representative sample.

Russian manipulation of energy prices in Eastern Europe from 1990-2015

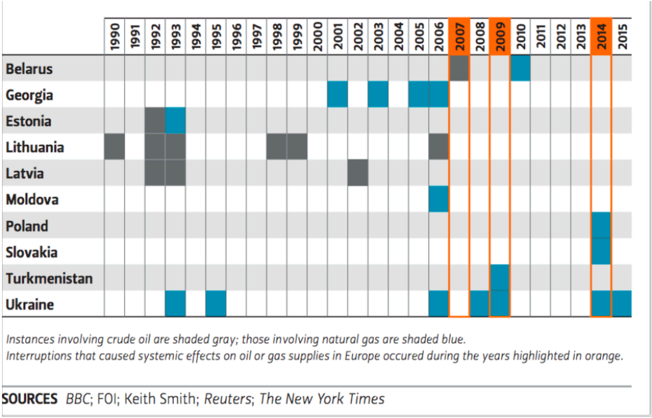


Figure 1: Known or likely politically based Russian price manipulation of oil or gas supply prices of former USSR countries 1990-2015 [13]

Ukrainian pipeline network as a central transit hub

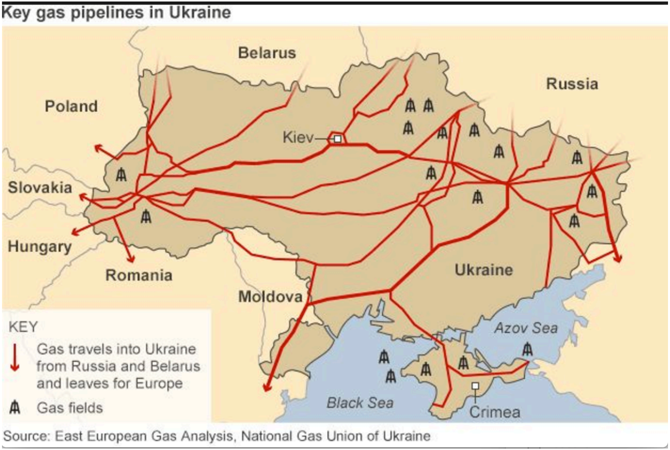


Figure 2: Natural gas pipelines in Ukraine

Methodological Solutions

1. Representative sample reduces selection bias & potential confounding factors.
2. Structured interview techniques to minimize recall bias focused on significant changes in self-reported depression, anxiety, and civilian PTSD.
3. Statistical techniques used to accommodate mixed sampling frequencies in ragged-edged datasets.
4. Multivariate time series methods to handle highly correlated endogenous series.
5. Used structural breaks with blip-indicators and level-shift variables to control for event impacts.
6. Truncate estimation prior to 2006 to circumnavigate confounding with endogenous time series
7. Forecast over the last five years to obtain measures assuming there had there been no Great Recession and no 3 week Russian gas-cut-off starting on Jan 1, 2009.

Operationalizing principal exogenous variables

1. Reconstruction of external exposure to radiation: measured by ^{137}Cesium.
2. Self-reported perceived risk of radiation exposure in three periods of time.
3. Mixed frequency analysis.
4. Panel data converted to time series.
5. Early cessation of estimation (prior to gas cut-offs).

Variable index I

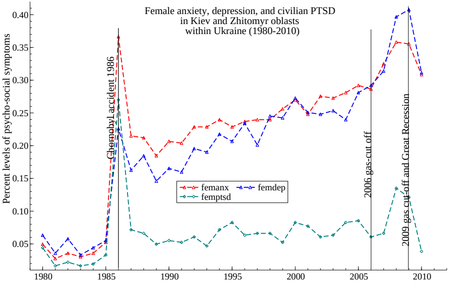
Principal endogenous time series

1. **fdepanx2**: Annual mean female of depression and anxiety scales.
2. **fptsdmc**: Annual mean female PTSD respondent reports.
3. **mdepanx2**: Annual male mean of depression and anxiety scales.
4. **mptsdmc**: Annual male mean PTSD respondent reports.

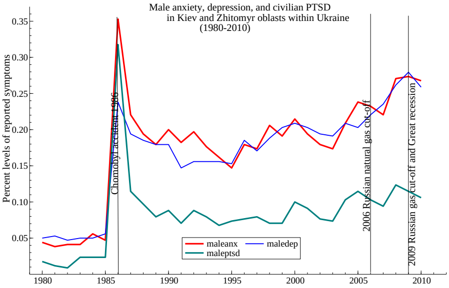
Female and Male explanatory variables & event indicators

- **frpre2**: female rescaled perceived risk of exposure to Chornobyl radiation.
- **mrpre2**: male rescaled perceived risk of exposure to Chornobyl radiation.
- **chornblip**: 1986 dummy variable for year of Chornobyl accident.
- **D.chornblip**: First difference of year of 1986 indicator variable.
- **ussrfall** : indicator variable, coded 1 if year $= 1991$, and 0, otherwise.
- **ussrlev**: level shift variable, coded 1 if year > 1991, and 0, otherwise.
- **chornblip**: Chornobyl indicator, coded 1 if year $= 1986$, and 0 otherwise.
- **dlnfpdisl**: 1st difference of natural log of annual mean percent of female pain and/or somatic discomfort.
- **dlnmpdisl**: 1st difference of natural log of annual mean percent of male pain and/or somatic discomfort.

Real Trajectories of Anxiety, Depression, and Civilian PTSD in Ukraine 1980-2010



Responses from Females



Responses from Males

Correlations and reliabilities of key constructs

Table 1: Time series correlations and item-other α reliabilities (in red)

α reliabilities correlations	female anxiety	female depression	female PTSD	male anxiety	male depression	male PTSD
female anxiety	0.923					
fem depression	0.949	0.940				
fem PTSD	0.669	0.512	0.956			
male anxiety	0.947	0.843	0.669	0.921		
male depression	0.969	0.939	0.943	0.948	0.926	
male PTSD	0.746	0.702	0.590	0.863	0.702	0.947

The α reliabilities displayed in Table 1 justifies the use of a common local level in the Multivariate State Space models.

Models Compared

- State Space Models
- VAR applied after LASSO
- VAR applied after adaptive LASSO
- VAR applied after Weighted Lag Adaptive LASSO
- Models compared with various numerical measures of accuracy

State Space Models

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State space model advantages

- Use variables with different sampling frequencies.
- Model untransformed variables [23], [6].
- Uses a diffuse prior
- Model highly correlated psychosocial distress and post-traumatic stress as endogenous variables.
- In our State Space models civilian PTSD is dependent on our Psychosocial distress scale (Depression/anxiety).
- Due to correlation between anxiety and depression, a new variable called "distress", which is the average of anxiety and depression, was created.
- Model male and female measures separately.

State Space Model Characteristics

1. A diffuse prior was employed.
2. A multivariate state space model for females with common levels.
3. The female measurement model Y = level + irregular + explanatory variables + interventions.
4. A multivariate state space model for males with common local levels.
5. The male measurement model Y = level + irregular + explanatory variables + interventions [6].

State space model equations

Measurement equation is

$$y_t = \mu_{\mathbf{0}} + \sum_{i=1}^{k} B_i x_{t-i} + \sum_{j=1}^{h} \omega_{j,t} I_t + \epsilon_t \quad \epsilon_t \sim NID(0, \sum_{\epsilon}) \tag{1}$$

where $\mu_{\mathbf{0}}$ = a k x 1 local level vector, η_t = innovation of the transition equation, y_t= an observed endogenous variable, x_{it} = an observed exogenous variable, I_t = an intervention blip or level shift, ϵ_t = a measurement error vector.
$\phi_i,\ B_i, and\ \omega_{j,t}$ are unknown parameters to be estimated, with $cov(\eta_t, \epsilon_t) = 0$.
The Transition equation is :

$$\mu_{\mathbf{t+1}} = \boldsymbol{\Theta}\mu_{\mathbf{t}} + \eta_{\mathbf{t}} \quad \eta_{\mathbf{t}} \sim \mathbf{NID(0}, \sum_{\eta}) \tag{2}$$

where *ta* is an NxK matrix of standardized factor loadings, $\mu_{\mathbf{t}}$ is a local level latent variable vector, the first N-K elements of which are zero and the K remainder are contain the local level μ_t, $\sum_{\eta_t}$ and $\sum_{\epsilon_t}$ are both NxN diagonal error variance matrices uncorrelated with one another at all time periods.

Dynamic common factor components

When r of the components of highly correlated, and the $rank(\sum_c) = r < p$, where p = the number of variables, the r components can be expressed in terms of their c common factors, such that

$$\sum_c = A \sum_c A' \tag{3}$$

where A is an r x r factor loading matrix and $\sum_c$ is a p x r matrix.

- Handle common trends in multivariate matrices.
- Allow PTSD to be dependent on the depanx2 scale [23].
- The level variance consists of one common factor, for male and female models, explaining 100% of the variance.
- The female error variance is about 89% explained by the distress and 11% by PTSD error variance.
- The male psycho-social (dep/anx) distress explains almost 100% of the male common variance.

Effects for Females in final state at time 2005

The perceived risk of radiation exposure is s driving factor in the prediction of psychosocial distress and civilian PTSD.

Neither the female nor the male model supported significant level breaks at 1991, when the USSR collapsed.

Table 2: DepAnxiety regression effects, $Rd^2_{fdepanx2} = 0.919$

	Coefficient	RMSE	t-value	Prob
chornblip 1986	0.049	0.006	7.976	[0.000]
Level Break 1998	0.015	0.004	4.018	[0.001]
frepre2	0.022	0.005	4.793	[0.000]

Table 3: PTSD regression effects, $Rd^2_{femptsd} = 0.974$.

	Coefficient	RMSE	t-value	Prob
chornblip	0.216	0.011	18.901	[0.000]
frepre2	0.095	0.005	3.575	[0.016]

(Rd^2 formula is in Appendix B)

Effects for Males in final state during 2005

Table 4: DepAnxiety regression effects, $Rd^2_{mdepanx2} = 0.968$

	Coefficient	RMSE	t-value	Prob
Outlier 1997(1)	-0.005	0.002	-2.549	[0.020]
Level break 1996(1)	0.009	0.002	4.688	[0.000]
Level break 1998(1)	0.006	0.003	2.175	[0.043]
Level break 2004(1)	0.012	0.003	3.554	[0.002]
chornblip	0.049	0.004	13.585	[0.000]
mrpre2	0.029	0.003	9.429	[0.000]

Table 5: PTSD regression effects, $Rd^2_{maleptsd} = 0.945$

	Coefficient	RMSE	t-value	Prob
Level break 2004(1)	0.034	0.009	4.022	[0.001]
chornblip	0.230	0.011	20.638	[0.000]
mrpre2	0.059	0.005	11.804	[0.000]

Female multivariate state space models: *Ex post* forecast evaluation

Use observations from 1998-2005 to evaluate the model.
There is no evidence of a statistically significant difference between our estimates and the actual data within this segment.

Table 6: Forecast accuracy measures from 1998 through 2005

Response	ME	RMSE	MAE	MPE	MAPE	SMAPE†
DepAnx	-2.603825	2.607	2.604	-3853.02	3853.02	11.88
PTSD	-8.5e-09	2.9e-08	2.6e-08	-0.00029	0.00037	0.000015

† SMAPE formula is in Appendix A.

Male multivariate state space models: *Ex post* forecast evaluation from 1998 through 2005

Use observations from 1998-2005 to evaluate the model.
There is no evidence of a statistically significant difference between our estimates and the actual data within this segment.

Table 7: Forecast accuracy measures for separate response variables.

Response	ME	RMSE	MAE	MPE	MAPE	SMAPE
Dep/Anx	-0.3354	-0.370	2.604	0.335	.-799.749	1.4e-06
PTSD	-7.5e-09	2.562-08	2.33e-08	-0.00012	0.0002	9.88-e06

Multivariate State Space *ex ante* female forecast profiles

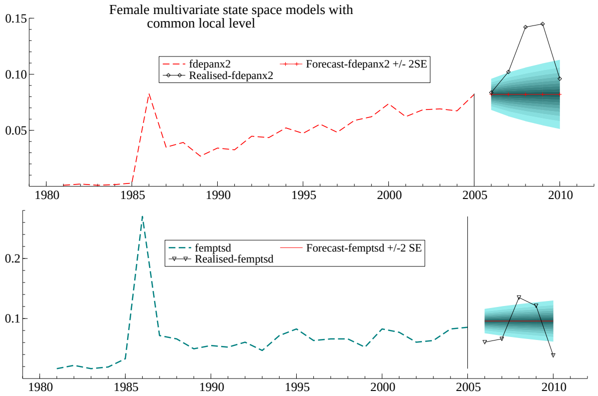


Figure 3: Female multivariate model forecast

Multivariate State Space *ex ante* male forecast profiles

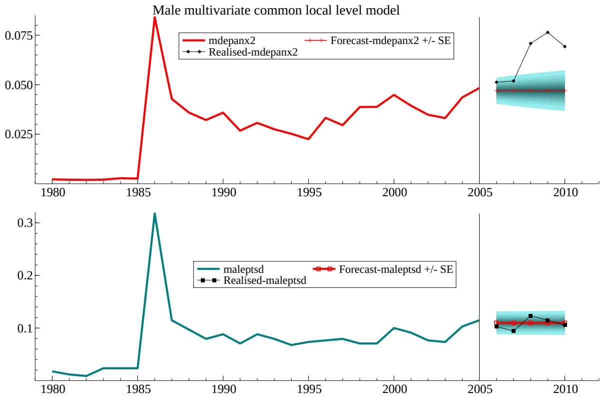


Figure 4: Male multivariate model forecast

Ex ante forecast evaluation for females from 2005 onward

Table 8: Forecast accuracy measures with depression/anxiety as a response

Year	Forecast	Forecast error	Std. Error	RMSE	RMSPE	MAE	MAPE	. SMAPE
2006	0.076	-0.001	0.006	0.007	0.877	0.007	8.774	. .
2007	0.076	-0.026	0.007	0.019	1.889	0.017	17.007	.
2008	0.076	-0.066	0.008	0.041	3.085	0.033	26.764	. .
2009	0.076	-0.069	0.009	0.049	3.569	0.042	31.904	. .
2010	0.076	-0.020	0.010	0.045	3.322	0.037	29.631	. 19.850

Table 9: Forecast accuracy measures with PTSD as a response

Year	Forecast	Forecast error	Std. Error	RMSE	RMSPE	MAE	MAPE	SMAPE
2006	0.013	0.020	0.012	0.020	28.554	0.020	285.540	.
2007	0.013	0.015	0.012	0.018	68.427	0.018	605.080	.
2008	0.013	-0.054	0.013	0.034	56.063	0.030	430.184	. .
2009	0.013	-0.040	0.013	0.036	48.698	0.032	341.474	.
2010	0.013	0.042	0.014	0.037	44.038	0.034	302.239	19.01

Ex ante forecast evaluation for males from 2005 onward

Table 10: Forecast accuracy with depressionanxiety as response

Year	Forecast	Forecast Error	Std. Error	RMSE	RMSPE	MAE	MAPE	SMAPE
2006	0.047	-0.004	0.004	-0.004	0.822	0.004	8.218	.
2007	0.047	-0.005	0.005	-0.005	0.881	0.005	8.792	.
2008	0.047	-0.024	0.005	-0.024	2.068	0.011	17.056	.
2009	0.047	-0.029	. 0.006	-0.029	2.627	0.016	22.404	.
2010	0.047	-0.022	0.006	0.020	2.754	0.017	24.342	20.05

Table 11: Forecast accuracy measures with PTSD as a response variable

Year	Forecast	Forecast Error	Std. Error	RMSE	RMSPE	MAE	MAPE	SMAPE
2006	0.027	0.007	0.013	0.007	3.537	0.007	35.373	.
2007	0.027	0.016	0.013	0.012	10.609	0.011	90.591	.
2008	0.027	-0.014	0.014	0.013	8.881	0.012	71.697	.
2009	0.027	-0.005	0.014	0.011	7.729	0.010	57.608	.
2010	0.027	0.004	0.014	0.010	6.959	0.009	49.634	. 3.51

Vector Autoregression Models

- Anxiety, Depression, and PTSD are highly correlated.
- It is possible that there is a “feedback loop” among them.
- This loop is likely driven by other variables
- There are only 25 observations (1980 - 2005) and 19 variables.
- Need a method to reduce number of variables
- Enter LASSO, adaptive LASSO and Weighted lag adaptive LASSO
- We apply each method as a selection operator and the obtain forecasts using selected variables with VAR.

LASSO Equation

Tibshirani (1996) proposed the Least absolute shrinkage and selection operator (LASSO)

$$\hat{\beta}^{LASSO} = argmin_{\beta_0,\beta_1,\ldots,\beta_k} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 \tag{4}$$

subject to $\sum_{j=1}^{k} |\beta_j| \leq t$. t is a tuning parameter, usually chosen by cross-validation, that controls how much each coefficient is "shrunk" toward zero.

Adaptive LASSO Equation

Zou (2006) proposed the adaptive LASSO, which employs different weights (ω_j) to different coefficients:

$$\hat{\beta}^{adaLASSO} = argmin_{\beta_0,\beta_1,\ldots,\beta_k} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 \tag{5}$$

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

Weighted Lag Adaptive LASSO Equation

Konzen and Ziegelmann (2016) proposed the weighted-lag adaptive LASSO, which employs different weights (ω_j) on coefficients and imposes penalties to coefficients on higher lagged covariates.

$$\hat{\beta}^{WLadaLASSO} = argmin_{\beta_0,\beta_1,\ldots,\beta_k} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 \tag{6}$$

subject to $\sum_{j=1}^{k} \omega_j |\beta_j| \leq t$, where $\omega_j = \left(|\hat{\beta}_j^{ridge}| e^{\alpha l} \right)^{-1}$, where $\alpha \geq 0$ is a smoothing parameter and l is the lag order.

Procedure

- Regression methods applied to males and females separately.
- Only time series used - no panel data employed.
- $T = 30$ and $p = 15$ (four variables deleted due to similarity in values)
- Variables with coefficients ≥ 0.001 were left in the model.
- VAR run with selected variables from 1980 - 2005. Accuracy measures tested with data from 2006 to 2009.
- ME, RMSE, MAE, MPE, MAPE, and MASE calculated.

Variables chosen for each model with associated coefficients

Response variable: Distress

Table 12: Variables and coefficients for LASSO-based models. These are coefficients, not p-values.

Gender	LASSO	Adaptive LASSO	WL LASSO, lag = 1	WL LASSO, lag = 2
Males	Workhealth (0.002) Homelife (0.003) Somatic (0.007)	Smoke, lag 1 (0.002) Somatic, lag 1 (0.015) Workhealth, lag 1 (0.004)	Distress, lag 1 (0.719) PercRisk, lag 1 (2.404) Doctor (0.052) Homehealth (0.040) Drink , lag 1 (0.178) Pain (0.068) Smoke (0.067)	Distress, lag 1 (0.032) PercRisk, lag 1 (9.239)
Females	Somatic (0.012)	Homehealth (-0.011) Interests (-0.007) Weekend (0.021) Drink (0.165) Smoke (-0.004) Somatic (0.008)	Distress, lag 1 (0.970) PercRisk, lag 1 (1.663) Homehealth (0.027) Pain (0.044) Smoke (-0.010)	Distress, lag 1 (0.036) PercRisk, lag 1 (12.838)

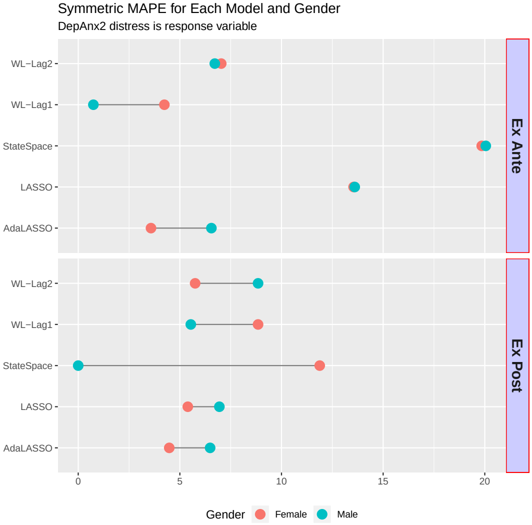
Variables chosen for each model with associated coefficients

Response variable: PTSD

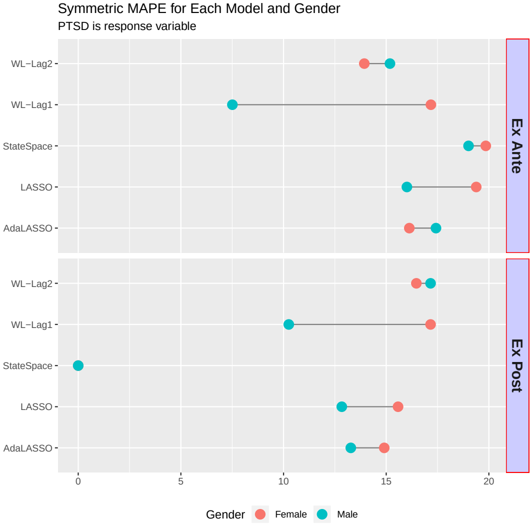
Table 13: Variables and coefficients for LASSO-based models. These are coefficients, not p-values.

Gender	LASSO	Adaptive LASSO	WL LASSO, lag = 1	WL LASSO, lag = 2
Males	PercRisk(-0.789) Doctor (0.003) Weekend (0.021)	Doctor (0.041) Homeheath (0.004) Workhealth (-0.013) Weekend (0.014) HomeLife (0.008) Sex (-0.006) Pain (-0.043) Smoke (0.002) Somatic (0.010)	PTSD, lag 1 (0.229) PercRisk, lag 1 (1.221) Drink, lag 1 (0.178)	PTSD, lag 1 (0.419) PercRisk, lag 1 (2.519)
Females	Doctor (0.095) Somatic (0.012)	Doctor (0.059) Homehealth (-0.011) Workhealth (-0.003) Social (0.001) Weekend (0.031) HomeLife (0.002) Sex (-0.005) Interests (0.002) Smoke (-0.008) Somatic (0.008)	PTSD, lag 1 (0.494) PercRisk, lag 1 (1.95) Interests, lag 1 (-0.008) Doctor, lag 1 (0.023)	PTSD, lag 1 (0.312) PercRisk, lag 1 (2.609) Drink, lag 1 (0.178) Pain, lag 1 (0.071)

Model Accuracy Measures, Psychosocial (Anx/Dep) Distress as response



Model Accuracy Measures, PTSD as response



Comparison of Methods

- LASSO and its variations outperformed State Space in *ex post* modeling.
- Coefficient estimates from LASSO and associated methods are unstable due to small sample size.
- Adaptive LASSO seems to overselect for variables
- LASSO variations are viable for variable selection leading to a subsequent model (VAR or ETS or LM) for longer series.
- All models, except adaptive LASSO, chose perceived risk as a significant contributor to PTSD and Psychosocial Distress, for both males and females. Somatic complaints are also a large contributor to both Distress and PTSD.
- State Space models outperformed others in *ex ante* forecasts.
- State Space models may be better for shorter series with low variability

New Contributions

1. Randomized selection of phone numbers in Kiev and Zhytomyr Oblasts in Ukraine to obtain a representative sample of general public opinion.
2. Applied multivariate time series models to overcome problems that confound analysis by highly correlated endogenous variables.
3. Tests found no evidence of the BHG hypothesis of an entangling effect of the collapse of the USSR.
4. Estimated only prior to the instance of the first natural gas cut-off event in January 2006.
5. Used a scenario forecast over a horizon of 2006 though 2010 to estimate what might have been had there been no change in the environment over that forecast horizon.
6. Focused on the general public rather than clean-up workers.
7. Used self-reported endogenous variables, exhibiting high reliability scores (with Cronbach's $\alpha > 0.7$) that were representative of Ukrainian beliefs and emotions at the time referenced (see Table 1).

Potential applications in Public health planning for post-disaster mitigation

1. The general population appears to have little biologically reactive levels of radiation exposure,
2. Most effects experienced are psycho-social.
3. Method can be applied retrospectively when the disaster has taken place 25 or more years before.
4. Predicted with reasonable accuracy the level of self-reported civilian PTSD for women and especially for men with perceived risk of exposure to disaster-related pollution.
5. Fear of being exposed is a significantly strong driver of the psycho-social distress as well as post-traumatic distress [38]
6. Controlled for potentially confounding events of Russian gas cut-offs in 2006 and 2009, and their impact on the energy and economic security of Ukraine.

Confirmed findings in the literature

- Primary driver of the psycho-social effects experienced after the Chornobyl accident is the *perceived* Chornobyl-related risk of radiation exposure in both males and females.
- The reconstructed cumulative average of external exposure drops out of the parameter vectors of our final models displayed in Tables 17, 2, 3, and 4 above.

Bias control

- Randomly selected respondents
- Stratify by gender
- Applied special memnonic measures.
- Back-translation verification.
- Four call-backs for each respondent.
- Tested for psychosocial impacts of major external events
- Control for major external events by early termination of estimation.

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Appendix A: *Ex ante* SMAPE for female models

- Very small forecast errors generate tiny denominators in MAPE computations, thus greatly inflating them.
- We observe small forecast errors coupled with grossly inflated MAPEs for the female PTSD scores: ranging from 286 to 605 %.
- To compensate for the scale dependency we compute the symmetric MAPE (SMAPE) for this 5 period horizon.
- We use the following formula:

$$SMAPE = \frac{100}{h} * \sum_{h=1}^{H} \frac{|Forecast - Actual|}{|Forecast + Actual|} \tag{7}$$

  where h = length of forecast horizon, H = final period of forecast horizon (5 years).

- For the female fdepanx2 forecast, the SMAPE = 18.316%, whereas the SMAPE for the female PTSD *ex ante* forecast = 19.008%.

Appendix B: Harvey's Goodness of fit: Rd^2

- The model fit for both equations is very high as can be observed from the Rd^2, defined as

$$Rd^2 = 1 - \frac{SEE}{\sum_{t=1}^{T} (\Delta y - \overline{\Delta y})^2}$$

where SEE = the sum of squared errors and the denominator is the sum of squared mean deviation of first differences [1].