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Supplementary appendix

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Supplementary Text for

Suicide mortality in US counties: a modeling study

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Appendix Text 1: Detailed description of independent variables

Proportion of population living in poverty; median household Income

US Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program(1) provides annual estimates of measures of income and poverty at small geographical resolutions (county and school district), which are either unavailable or only available infrequently. For example, the 1-year American Community Survey (ACS) provides data on persons living in poverty only for counties with a population greater than 65000. SAIPE uses a regression model to estimate poverty rates in all counties with the number of persons in poverty as the dependent variable (in counties where ACS survey estimates are available) and multiple predictor variables from the Supplemental Nutrition Assistance Program (SNAP), federal income tax returns and US Decennial census. Estimates of median household income are similarly obtained from a separate regression model with additional predictor variables provided by the Bureau of Economic Analysis.

Prevalence of major depressive episodes

The National Surveys on Drug Use and Health (NSDUH) dataset contains state-level small area estimates on key substance use and mental health outcomes(2). The depression prevalence indicator is the estimated proportion of population with at least one major depressive episode during the previous year. As county-level estimates of prevalence are not available from this data source and we are unaware of other reliable sources, the annual prevalence is assumed to be the same in all counties of a state.

State prevalence of firearm-owning households

RAND's Household Firearm Ownership Database(3) provides annual estimates of the proportion of adults who live in a household with firearms for each state in the US between 1980 and 2016. These estimates are based on direct measures of ownership from individual-level survey data and indirect proxy measures of ownership (for example, per capita hunting licenses, background checks, and subscriptions to *Guns & Ammo* magazine).

As the surveys were designed to be nationally representative but not for each state, multi-level regression with post-stratification was used to calculate subnational estimates(4) (A1). These corrected direct measures are then combined with indirect measures using a structural equation model which attempts to represent both direct and indirect measures as dependent in part on household ownership rates and in part on observed and unobserved confounders.

Additionally, as one of the indirect measures used by RAND (proportion of suicides that involved firearms) is collinear with the outcome of interest in this study, we re-estimated the firearm ownership rates with this measure excluded. Household firearm ownership rates were assumed to be homogenous across all counties in the state, a necessary simplification given annual county-level estimates of firearm ownership are unavailable.

Average weekly wage

The Bureau of Labor Statistics through the Quarterly Census of Employment and Wages program(5) provides timely and finely-resolved estimates of wages from several industries covering over 95% of US jobs. These estimates are based on employer reports to the unemployment insurance contribution system and two annual surveys. Data are aggregated to industry sectors and geographic levels (metro, county, state, and national) and are available at annual frequency, with more frequent releases available at higher aggregations. Here, we use county-wise estimates of annual average weekly wage across all industries.

Unemployment rate

The Bureau of Labor Statistics through the Labor and Unemployment Statistics (6) program provides estimates of unemployment by combining data from the Current Population Survey, the Current Employment Statistics survey, and state unemployment insurance systems. County-level rates incorporate methodological corrections to include agricultural workers, self-employed, unpaid family workers and private household workers who are not otherwise represented in administrative/survey datasets. These estimates are considered reliable and form the basis for budgetary allocations by federal, state and local governments.

Population Density

Annual population density in each county was estimated using the intercensal and postcensal population estimates described above and the county land area per the 2010 US census(7). This calculation is not sensitive to changes in county boundaries during the study period. A log transformation was applied as the distribution was found to be non-normal.

The estimates for some of the county-level variables in a small percentage of counties (< 2%) were missing from the original data sources. We used the following 3-step process to impute missing values: (a) the mean of neighboring (defined in later sections) counties that have estimates; (b) if there are no neighbors with estimates, the median of all counties in the state for which estimates are available; and (c) if estimates are missing for all counties in a state, the median across all counties in the US for which estimates are available.

Appendix Figure 1 shows pairwise Spearman correlation for each pair of covariates.

Appendix Text 2: Conditional Autoregressive (CAR) Models

Studies have previously used a wide array of regression and time series models to calculate effect estimates of suicide risk factors and/or predict future trends (8). Methods that are solely temporal (sARIMA, for example) do not capture the often critical spatial dependencies in suicides. Local spatial models, such as geographically weighted regression, estimate regression coefficients for different locations in space and have been used to understand spatial variations in regression relationship between an outcome of interest and covariates(9, 10). Global models, such as the CAR, on the other hand estimate a single set of global regression coefficients. The choice of CAR in this study is largely driven by our research objective, as stated in the main text.

A CAR model under Poisson distribution assumption is specified as:

$$y_{ct} \sim Poisson(\mu_{ct}\theta_{ct})$$

$$ln(\theta_{ct}) = \beta_0 + \boldsymbol{x}_{ct}^T\boldsymbol{\beta} + \psi_{ct}$$

$$\beta \sim N(\mu_\beta, \Sigma_\beta)$$

where y_{ct} denotes observed count of suicide deaths in county c during year t, μ_{ct} is the expected suicide deaths in county c in year t and θ_{ct} is the risk relative to μ_{ct} (see Appendix Text 3). $\boldsymbol{x}_{ct} = (x_{ct1} \ldots x_{ctp})$ is a vector of p covariates for county c during year t, with $c = 1, \ldots, C$ for the C counties in the US and $t = 1,\ldots,N$, for N years in the study period; $\boldsymbol{\beta} = (\beta_1 \ldots \beta_p)$ is the vector of covariate regression parameters whose Gaussian prior is defined by mean μ_β and diagonal variance matrix $\boldsymbol{\Sigma}_\beta$. ψ_{ct} a latent component encompassing one or more sets of spatiotemporally autocorrelated random effects. The CAR-ANOVA(11) model decomposes spatiotemporal variation, ψ_{ct}, into an overall spatial effect across the study period ($\boldsymbol{\phi}$), an overall temporal trend over the study area ($\boldsymbol{\delta}$), and a set of independent space-time interactions ($\boldsymbol{\gamma}$); $\boldsymbol{\phi} = (\phi_1 \ldots \phi_C)$ and $\boldsymbol{\delta} = (\delta_1 \ldots \delta_N)$ are modeled by the CAR prior proposed by Leroux and others (12).

$$\psi_{ct} = \phi_c + \delta_t + \gamma_{ct}$$

$$\gamma_{ct} \backsim N(0, \tau_I^2)$$

$$\phi_c | \phi_{-c}, \boldsymbol{W} \backsim N\left(\frac{\rho_S \sum_{j=1}^{C} w_{cj}\phi_j}{\rho_S \sum_{j=1}^{C} w_{cj} + 1 - \rho_S}, \frac{\tau_S^2}{\rho_S \sum_{j=1}^{C} w_{cj} + 1 - \rho_S}\right)$$

$$\delta_t | \delta_{-t}, \boldsymbol{D} \backsim N\left(\frac{\rho_T \sum_{j=1}^{N} d_{tj}\delta_j}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}, \frac{\tau_T^2}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}\right)$$

$$\tau_S^2, \tau_T^2, \tau_I^2 \backsim Inverse - Gamma\ (a, b)$$

$$\rho_S, \rho_T \backsim Uniform\ (0, 1)$$

Here, **W** is the C x C spatial adjacency matrix, with w_{cd} = 1 if counties c and d are adjacent to each other and 0 otherwise (counties are adjacent if they share at least one boundary point in the shape file; a county is not adjacent to itself). Analogously, ***D*** is the N x N temporal adjacency matrix, with d_{tj} = 1 if $|t - j|$ = 1 (i.e. consecutive years) and 0 otherwise. Note that **W** and **D**, are independent of the outcome. The priors for the spatial (τ_S^2), temporal (τ_T^2) and space-time interaction (τ_I^2) random effects variances are specified by an Inverse-Gamma distribution with *a=1* and *b=0.01*; spatial (ρ_S) and temporal (ρ_T) dependence parameters have uniform priors in the unit interval (1 indicates strong dependence; 0 independence). See appendix text 7 for sensitivity analysis on hyperparameters of the random effects variances.

The models were fit in a Bayesian setting using Markov chain Monte Carlo simulations. Parameters whose full conditional distributions have a closed form distribution are Gibbs sampled and the rest are updated using the Metropolis adjusted Langevin algorithm (13). For each model, three Markov chains each 110,000 in length with a burn-in of 10,000 were generated and a thinning factor of 1,000 was applied to remove correlation among the samples (14-16). Convergence was verified with the Geweke diagnostic statistic (17). Implementations of the methods are per CARBayesST package (18, 19) in R (20).

Appendix Text 3: Reference model

Let y_{ct} denote observed count of suicide deaths in county *c* during year *t,* and p_{ct} the corresponding population estimate. We assume the population can be split into *k* mutually exclusive and exhaustive strata, each with a different risk of suicide death; let y_{ctk}, p_{ctk} be the respective suicide deaths and population in strata *k*. The suicide risk for strata *k* nationally over the study period (*t=1…n*) is calculated as:

$$\eta_k = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{\sum_c y_{ctk}}{\sum_c p_{ctk}}\right)$$

The expected number of deaths in county *c* during year *t* is calculated as:

$$\mu_{ct} = \sum_k p_{ctk} * \eta_k$$

Drawing on prior studies on heterogeneity of suicide risk by age, race and gender, we use *k* = 72 strata of 9 age groups ([5, 15), [15, 25), …, 85+), 4 racial groups (White, Black, American Indian/Alaskan Native, and Asian/Pacific Islander) and two gender groups. The race and gender categories are identical to those provided by the bridged-race population datasets.

Appendix Text 4. Variable selection for the CAR model

To identify variables with marginal contribution to model quality, we built an exhaustive set of Poisson generalized linear models with the expected deaths (as described above in appendix text 3) as offset and all possible combinations of the 7 risk factors as explanatory variables. Specifically, we built 127 models ($2^7 - 1$), where in each model the observed deaths was the dependent variable and one combination of the risk factors were explanatory variables. We calculated goodness of-fit metric (Akaike Information Criterion (AIC)) for each model and compared these to the AIC of the *full* model, the model built using all available predictors. The figure below shows the difference in AIC of each model relative to the AIC of the *full* model for the best 30 models. Also shown in the figure are two additional goodness-of-fit metrics, demonstrating that the relative ranking of models was largely insensitive to the metric used.

Based on the AIC, we identified the best 6-, 5-, 4- and 3- predictor models to assess the tradeoff between model parsimony and model fit quality. We chose to use the best 5-predictor model (which excluded unemployment rate and the prevalence of major depressive disorder) as the *select* model, as it offered the possibility of dropping two variable with a slight (.07%) degradation in AIC

Figure T4F1: Goodness-of-fit metrics for different combinations of covariates. The full model using all 7 covariates had the best fit, and the difference (%) of all other models relative to the full model is shown for the top 30 models (per AIC).

Appendix Text 5: Isolated counties and counties with no recorded deaths

Of the 3142 counties in the US, 5 counties (Honolulu, HI; Kauai, HI; Hawaii, HI; Nantucket, MA; and San Juan WA) have no known neighbors in the shape file. As the CAR model specification requires each location to have at least one neighbor, these counties were excluded from the analysis. Additionally, two counties (Wade Hampton, AK and Shannon, SD) that had no outcome data were also excluded.

There were also a sizeable number of counties with no recorded deaths during a year. Over the 12-year study period, a total of 4979 county-year instances (13.2% of total) had zero suicide death counts, with the yearly percentages decreasing from 15.2% in 2005 to 10.6% in 2016. While the CAR models do not require any remediation for these instances, when the observed outcome is 0, the symmetric proportion error takes the maximum possible penalty of 1, thus considerably inflating the aggregate mean errors. As we are unaware of a consensus on how to handle these zero-count cases, we retained these counties while calculating the errors in the main text. Appendix Figure 7 shows the errors with these county-year instances excluded. Dropping these county-year pairs does not change the improvement in errors of all CAR-ANOVA models relative to the *reference* model.

Appendix Text 6. CAR model with only county-level covariates

Prior to building CAR models we built Poisson log-linear models and compared goodness-of-fit from all combination of covariates. This was done in part to avoid having to build a large number of computationally expensive CAR models, for identifying a good set of covariates. With these simpler models, we found that despite the strong assumption of intra-state homogeneity, both firearm ownership rate and prevalence of major depressive disorder were highly informative, and their non-inclusion considerably degraded AIC. In fact, the 5-covariate model that did not include these two variables underperformed (higher AIC) most 4-, and 3-covariate models and the univariate model with just the firearm ownership rates.

We have additionally built a CAR-ANOVA model using only county-level covariates. Effect estimates are shown in table below (appendix table T6T1). In the in-sample setting, the goodness-of-fit measure (WAIC) of this model (*select.ct*) was nearly identically to that of the *full* model and worse than that of the *select* model. Using the paired Wilcoxon signed rank test (appendix figure T6F1), errors were found to be not statistically significantly different from those of the *select* model, but lower than those of the *full* model. The model outperformed the *null* model by both WAIC and errors.

To summarize, the inclusion of these two variables in the CAR models *full* and *select,* under the assumption of intra-state homogeneity, did not unambiguously degrade model fit or errors. As an aside, the relative value of the covariates as assessed with log-linear models did not appear to translate to CAR models, possibly suggesting the strong effect of spatiotemporal autocorrelation compared to the effect of one or more of the considered covariates.

Variable	Mean Estimate	95% CI
Median HH income	-5.189	-6.38, -4.03
Population density	-0.022	-0.03, -0.01
Poverty, %	-0.519	-0.72, -0.31
Unemployment, %	0.890	0.54, 1.22
Weekly wage	0.008	-0.05, 0.07
rho.S	0.980	0.96, 0.99
rho.T	0.911	0.62, 0.99
tau2.I	0.003	0.002, 0.004
tau2.S	0.099	0.092, 0.108
tau2.T	0.003	0.002, 0.008
WAIC	161249	

Table T6T1: Effect estimates for suicide mortality risk for one standard deviation change in predictor, using five county-level models.

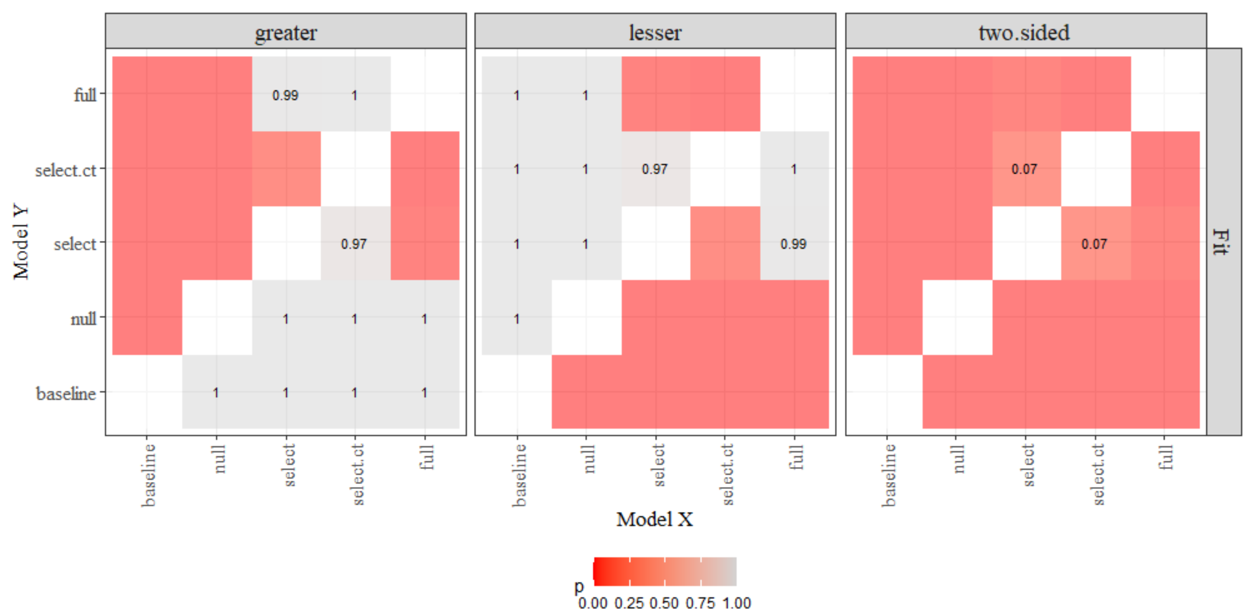

Figure T6F1: Wilcoxon signed rank test for each pair of models, as in Figure 2 of the main text, and now including CAR model (*select.ct*) built with only county-level variables. Significance (p < .05) in the 'two.sided' column indicates that the difference in errors of Model *X* and Model *Y* is not symmetric around 0. p < .05 in the 'lesser' panel column indicates errors in Model *X (x-axis)* are lower than Model *Y*. Actual p -value are shown as text when errors are not significantly different.

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Appendix Text 7. Sensitivity analysis of Inverse-Gamma shape and scale hyperparameters

As described in section 2, the priors for the random effects variances (τ_S^2, τ_T^2 and τ_I^2) were defined by an Inverse-Gamma distribution with shape=*1* and *scale=0.01.* To assess the sensitivity of the CAR model results to these priors, we built additional models with shape = {0.75, 1, 1.25} and scale = {0.005, 0.01, 0.02}, and same covariates as the *select* model.

Figure T7F1 plots the stanardized effect estimates for each of these 9 models, demonstrating no large changes. Figures T7F2 shows that there are differences in error among the 9 models, but overall have lower error than of the *full* model, as reported in the main results. Higher *scale* values appear to yield lower errors for the same *shape* and the difference is statistically significant.

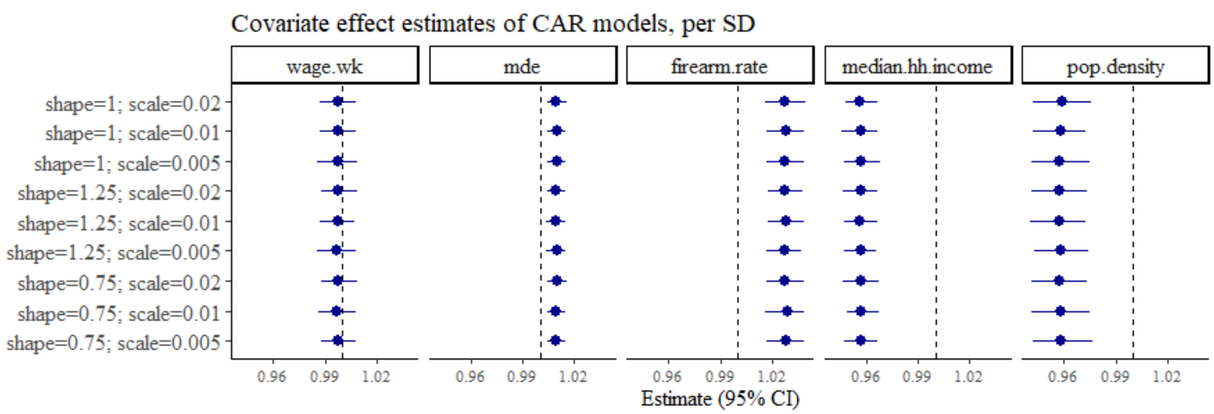


Figure T7F1: Standardized effect estimates for suicide mortality risk for the select CAR model, with 9 pairs of hyperparameters.

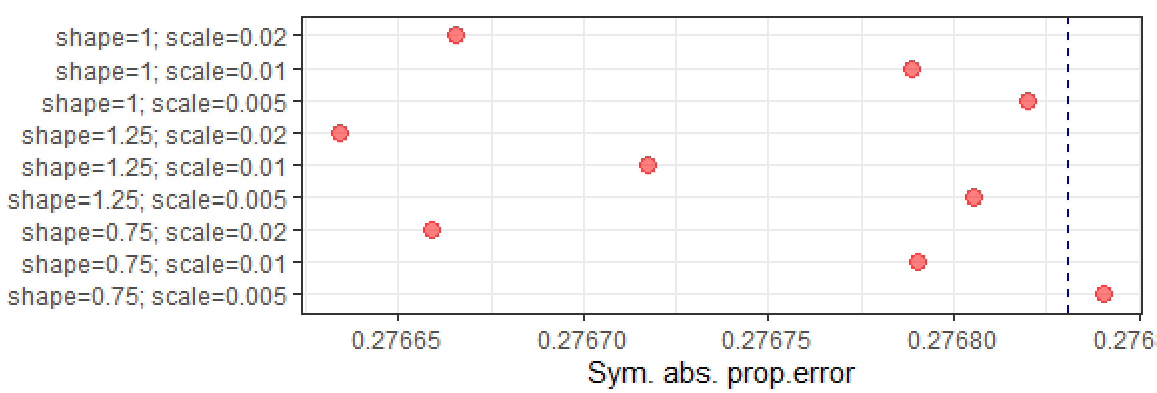


Figure T7F2: Symmetric absolute proportion error for the 9 models. Blue vertical represents error with the *full* model

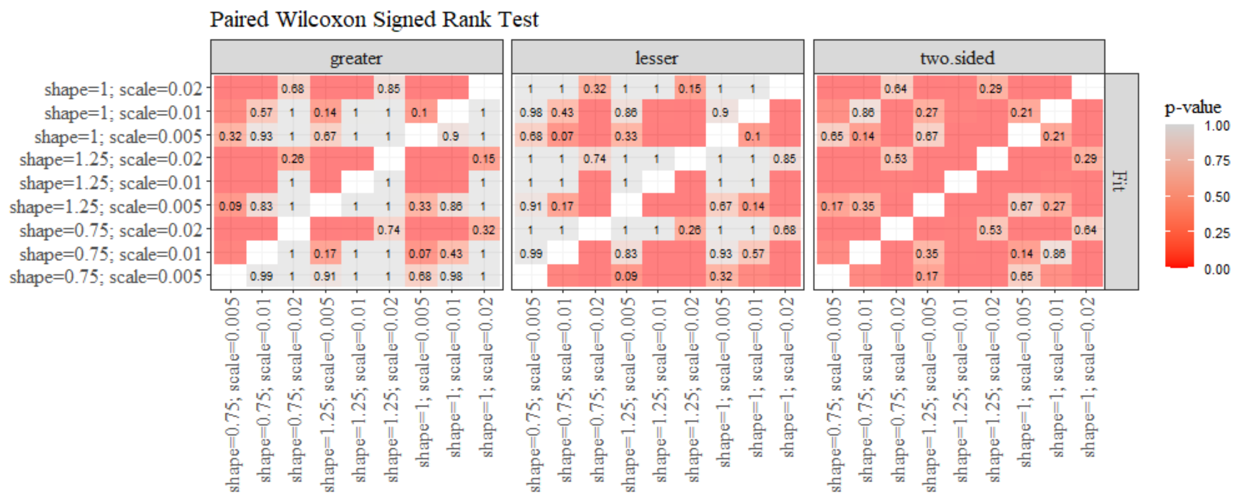


Figure T7F3: Wilcoxon signed rank test for significant differences in the errors.

Variable	Select	Full
Firearm ownership	1.0283 (1.018, 1.039)	1.03 (1.02, 1.041)
Major Depression, %	1.0099 (1.004, 1.015)	1.0102 (1.005, 1.016)
Median HH income	0.9575 (0.949, 0.968)	0.9413 (0.928, 0.955)
Population density	0.9574 (0.942, 0.975)	0.9629 (0.946, 0.98)
Poverty, %	NA	0.9664 (0.954, 0.98)
Unemployment, %	NA	1.028 (1.019, 1.038)
Weekly wage	0.997 (0.987, 1.007)	1.0017 (0.992, 1.013)

Appendix Table 1. Effect estimates for suicide mortality risk for one standard deviation change in predictor.

Variable	Mean Estimate	95% CI
Firearm ownership	0.246	0.16, 0.34
Major Depression, %	1.455	0.56, 2.19
Median HH income	-3.681	-4.42, -2.78
Population density	-0.024	-0.03, -0.02
Weekly wage	-0.019	-0.08, 0.04
rho.S	0.973	0.94, 0.99
rho.T	0.911	0.61, 0.99
tau2.I	0.003	0.002, 0.004
tau2.S	0.099	0.091, 0.108
tau2.T	0.003	0.001, 0.007
WAIC	161235	

a. *Select* model

Variable	Mean Estimate	95% CI
Firearm ownership	0.262	0.18, 0.36
Major Depression, %	1.500	0.73, 2.31
Median HH income	-5.149	-6.37, -3.96
Population density	-0.022	-0.03, -0.01
Poverty, %	-0.533	-0.74, -0.34
Unemployment, %	0.954	0.66, 1.27
Weekly wage	0.011	-0.05, 0.08
rho.S	0.975	0.94, 0.99
rho.T	0.914	0.61, 0.99
tau2.I	0.003	0.002, 0.004
tau2.S	0.096	0.088, 0.104
tau2.T	0.003	0.002, 0.008
WAIC	161250	

b. *Full* model

Variable	Mean Estimate	95% CI
rho.S	0.982	0.958, 0.995
rho.T	0.893	0.572, 0.987
tau2.I	0.003	0.002, 0.004
tau2.S	0.120	0.111, 0.129
tau2.T	0.002	0.001, 0.006
WAIC	161267	

c. *null* model

Appendix Table 2. Effect estimates in suicide mortality risk for one *unit change* in predictor, and spatial and temporal dependence parameters. WAIC: Watanabe-Akaike Information Criterion

Chain 1: WAIC= 161229;DIC = 161100; p.d. = 2613; LMPL = -80634

	Median	2.5%	97.5%	n.effective	Geweke.diag
(Intercept)	0.1505	0.0683	0.2427	100	-0.2
Weekly wage	-0.0189	-0.0818	0.045	100	-0.6
Median HH income	-3.5928	-4.4867	-2.6009	100	0.9
Major depression, %	1.4582	0.5275	2.1948	100	0.1
Firearm ownership	0.2369	0.1578	0.3238	149	0.9
Population density	-0.0252	-0.0323	-0.0154	73.6	-0.9
tau2.S	0.0991	0.0909	0.1081	100	0.5
tau2.T	0.0031	0.0012	0.0069	100	-0.7
tau2.I	0.0029	0.0022	0.0037	23	0.7
rho.S	0.9737	0.9466	0.9912	100	-0.3
rho.T	0.8983	0.5141	0.9902	100	0.6

Chain 2: WAIC= 161239; DIC = 161107; p.d. = 2619; LMPL = -80641

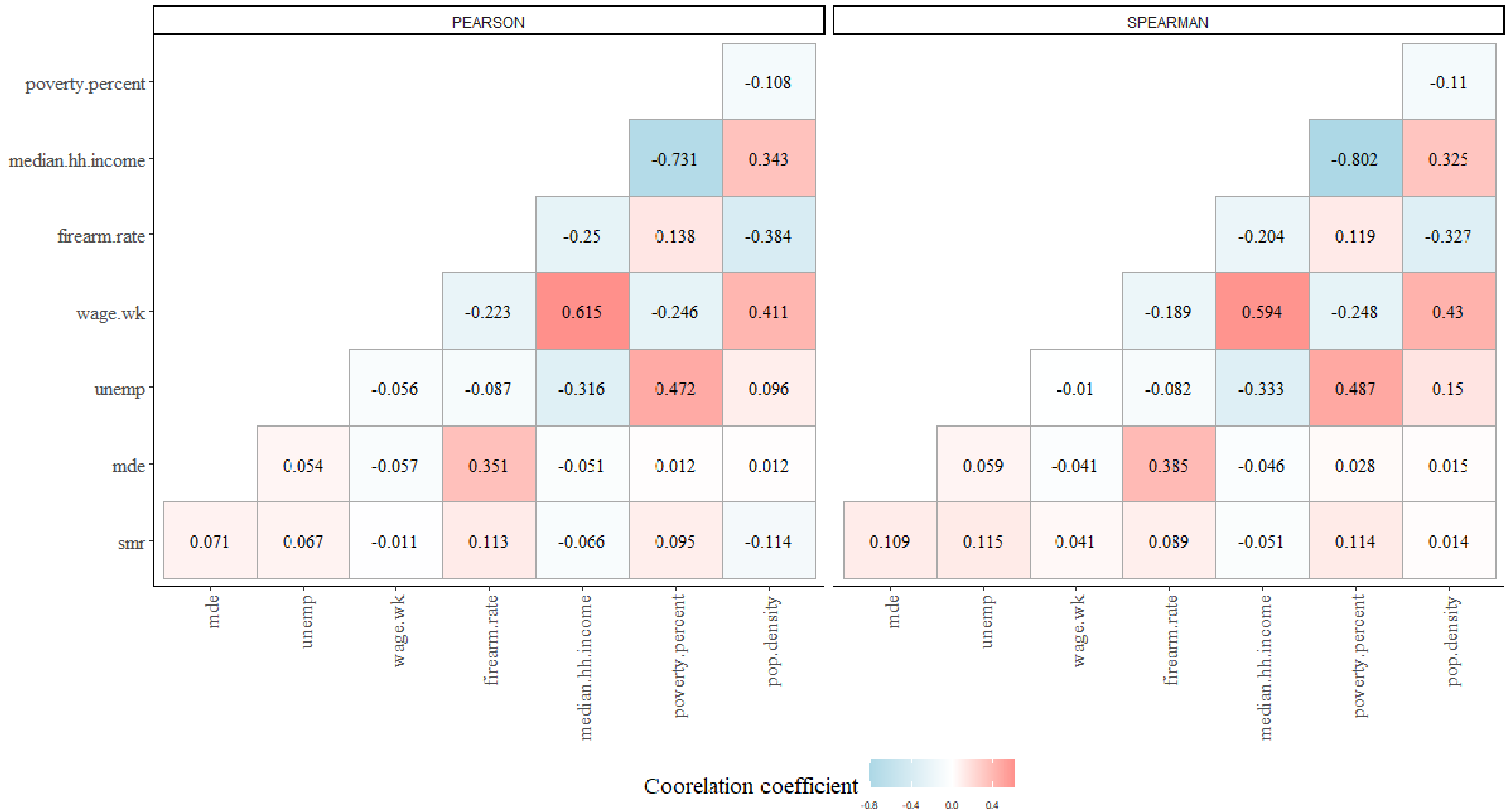
	Median	2.5%	97.5%	n.effective	Geweke.diag
(Intercept)	0.1447	0.0804	0.2158	100	-1.9
Weekly wage	-0.0166	-0.084	0.0357	100	-0.8
Median HH income	-3.7457	-4.4904	-2.7739	100	1.5
Major depression, %	1.5112	0.6544	2.263	100	-0.7
Firearm ownership	0.2527	0.1689	0.3581	100	1.3
Population density	-0.0244	-0.0331	-0.0162	100	2.6
tau2.S	0.0989	0.0913	0.108	100	2.1
tau2.T	0.0025	0.0013	0.0074	100	-0.1
tau2.I	0.003	0.0024	0.0037	49.2	1.1
rho.S	0.974	0.9379	0.9915	70.2	1.7
rho.T	0.9192	0.74	0.994	100	1.3

Chain 3: WAIC= 161239;DIC = 161115; p.d. = 2633; LMPL = -80645

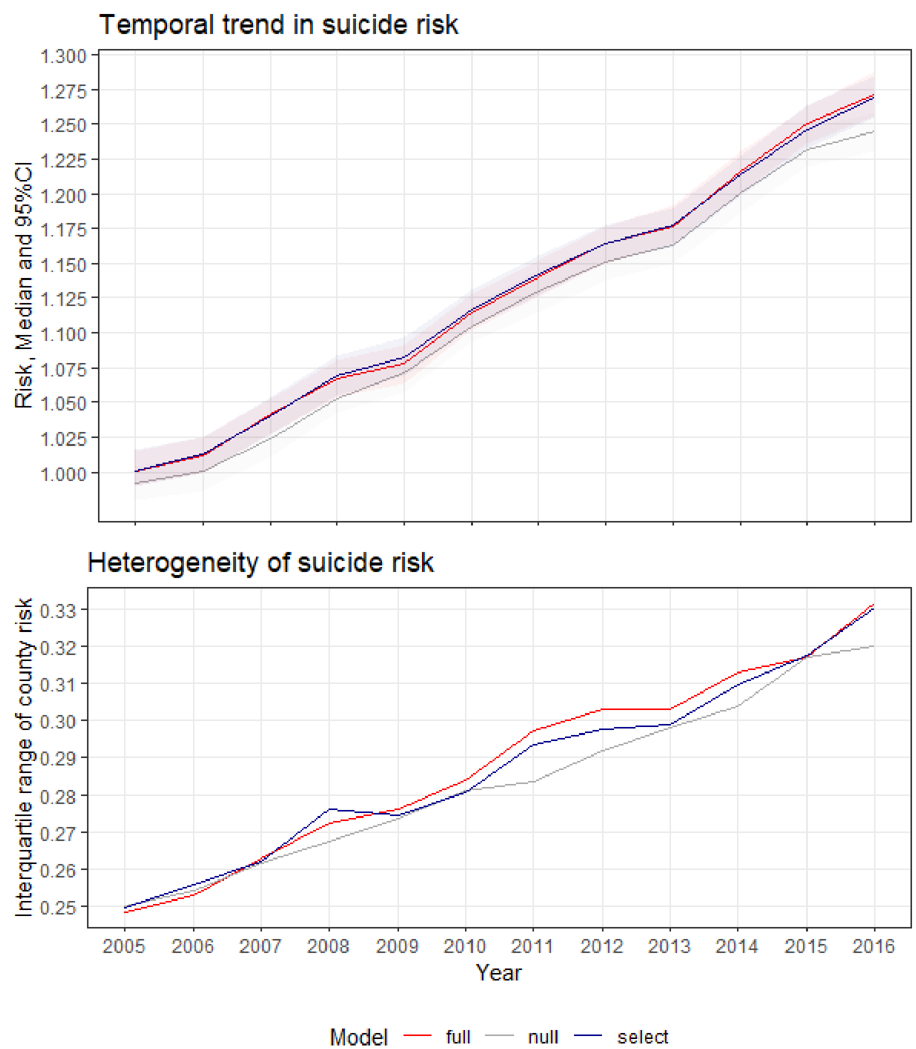
	Median	2.50%	97.50%	n.effective	Geweke.diag
(Intercept)	0.1534	0.0652	0.246	584	0.3
Weekly wage	-0.0203	-0.0793	0.0409	100	-0.4
Median HH income	-3.7046	-4.2836	-2.9766	100	0.8
Major depression, %	1.3949	0.4921	2.1189	100	-1.1
Firearm ownership	0.248	0.1489	0.3352	100	0.5
Population density	-0.0239	-0.0358	-0.0138	100	-0.3
tau2.S	0.0986	0.0903	0.1081	100	0.9
tau2.T	0.0029	0.0014	0.0065	100	0.4
tau2.I	0.003	0.0023	0.0037	50.3	0.6
rho.S	0.9712	0.9425	0.9902	100	-2.5
rho.T	0.9146	0.588	0.9899	100	-0.1

Gelman-Rubin Diagnostic: 1.02

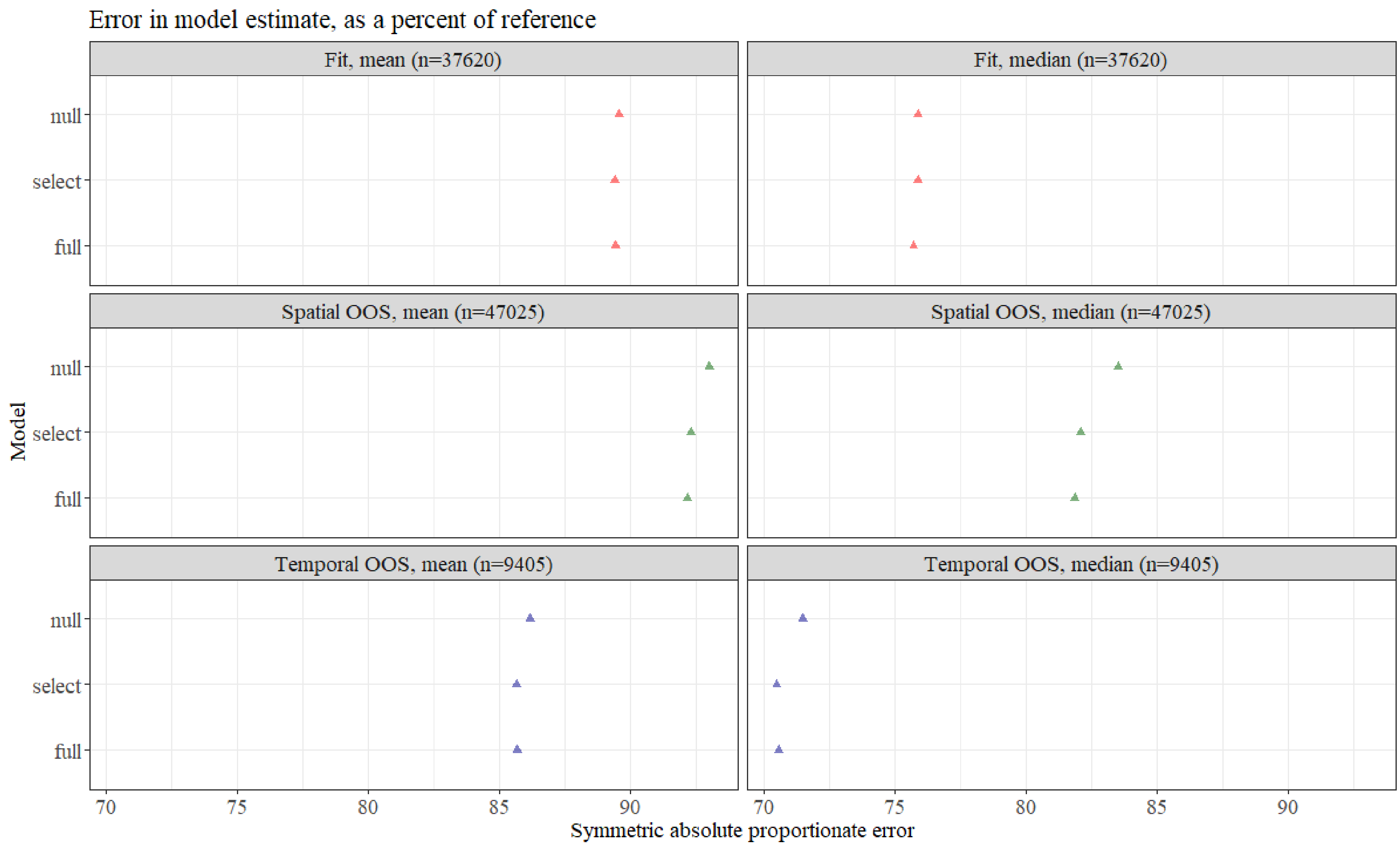
Appendix Table 3: Output from the s*elect* model over the fit period from three chains; showing mean and 95% credible interval; effective number of independent samples and diagnostics. Geweke diagnostic between [-2, 2] indicates model convergence and Gelman-Rubin statistic under 1.1 indicates that longer chains are not necessary. *WAIC*: Watanabe-Akaike Information Criterion *DIC*: deviance information criteria; *p.d.*: effective number of parameters; *LMPL*: Log Marginal Predictive Likelihood.



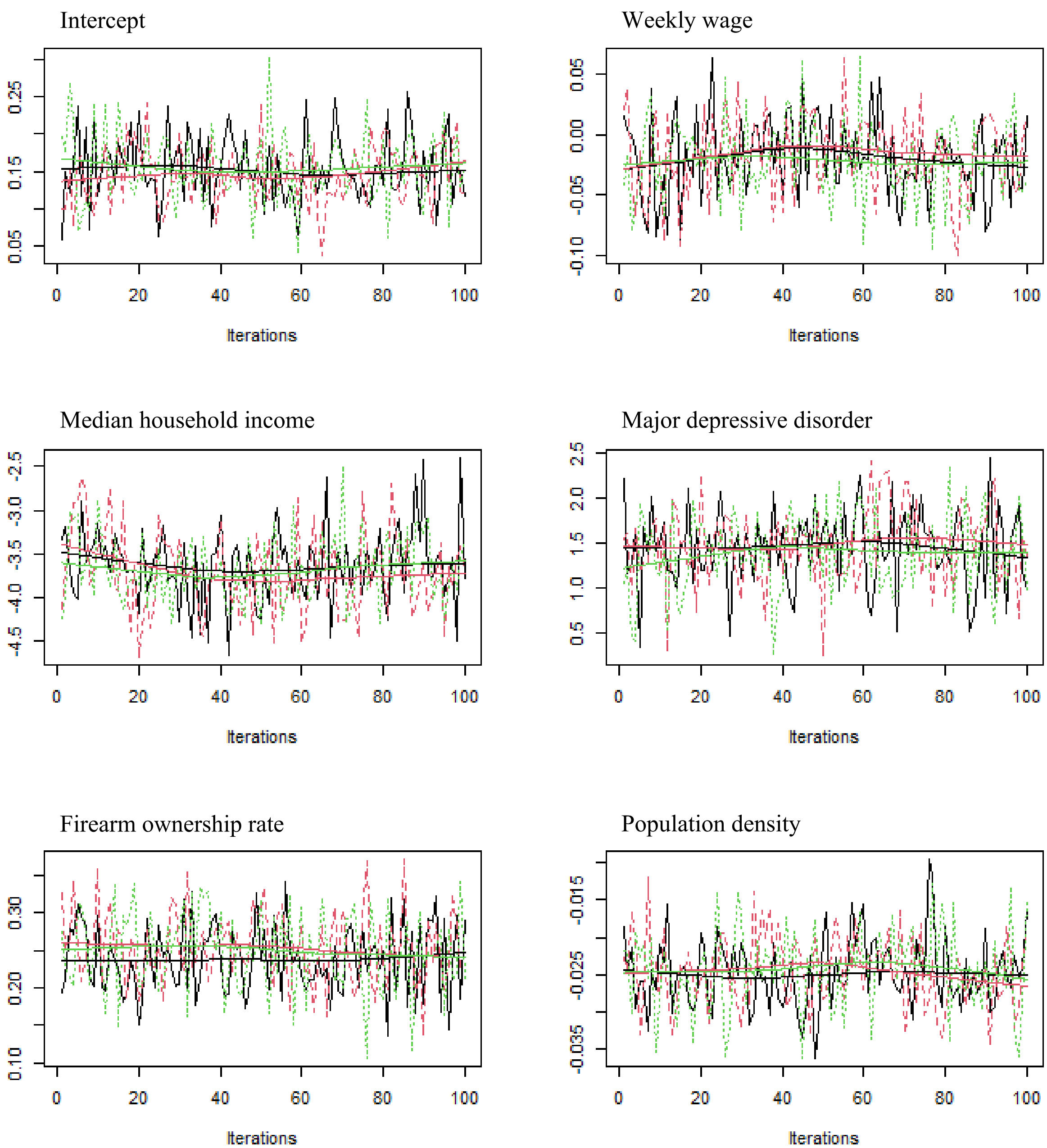
Appendix Figure 1. Pearson and Spearman correlation coefficient for variables used. *smr* = standardized mortality rate; *mde*: major depressive episode; *unemp*: unemployment rate; *wage.wk*: weekly wage; *median.hh.income*: median household income



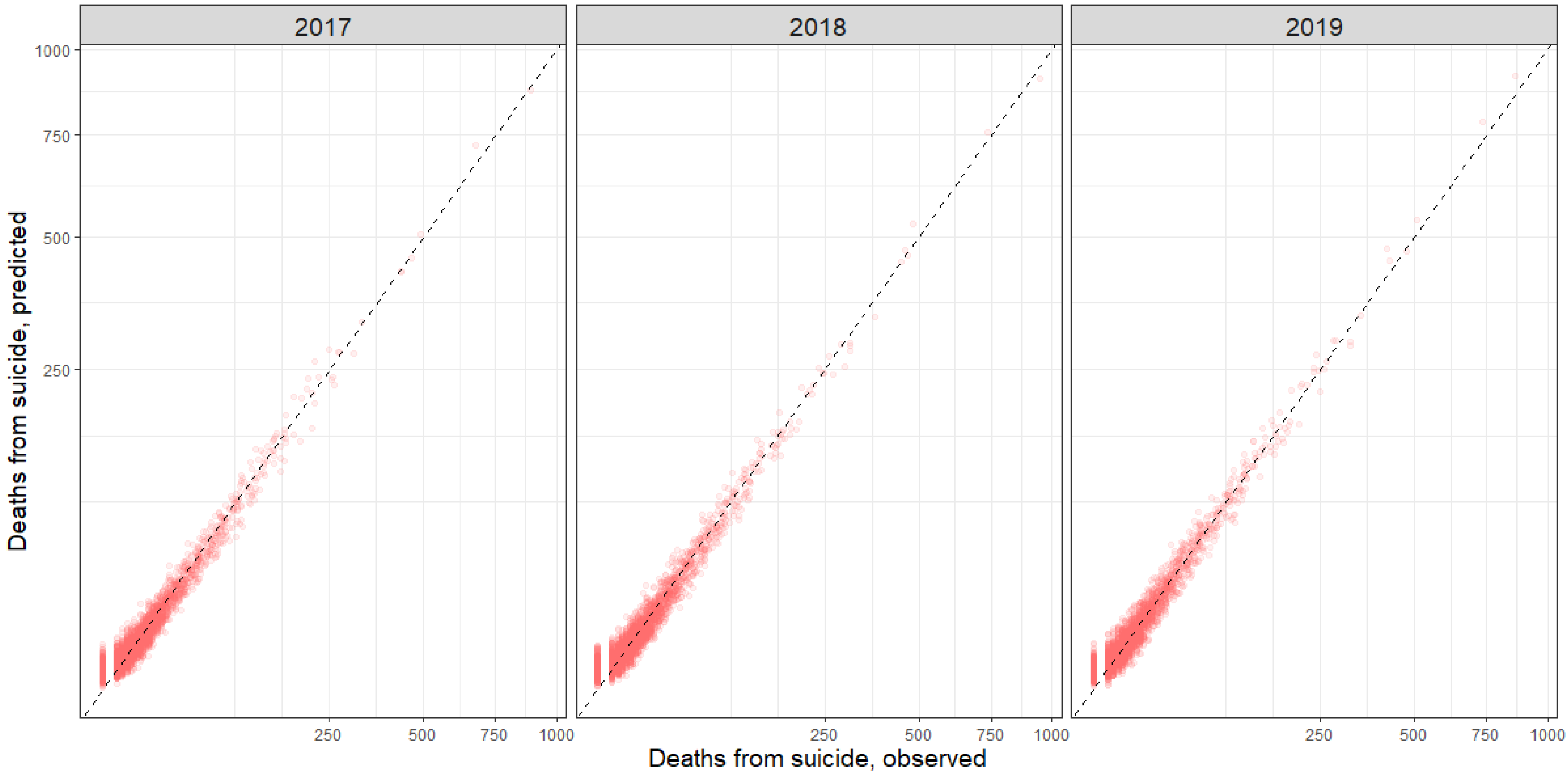
Appendix Figure 2. a) Median and 95% CI for national suicide risk for the three CAR models (risks from *select* and *full* models are similar and not distinguishable). B) Interquartile (IQR) range of county-level risk for the same models.



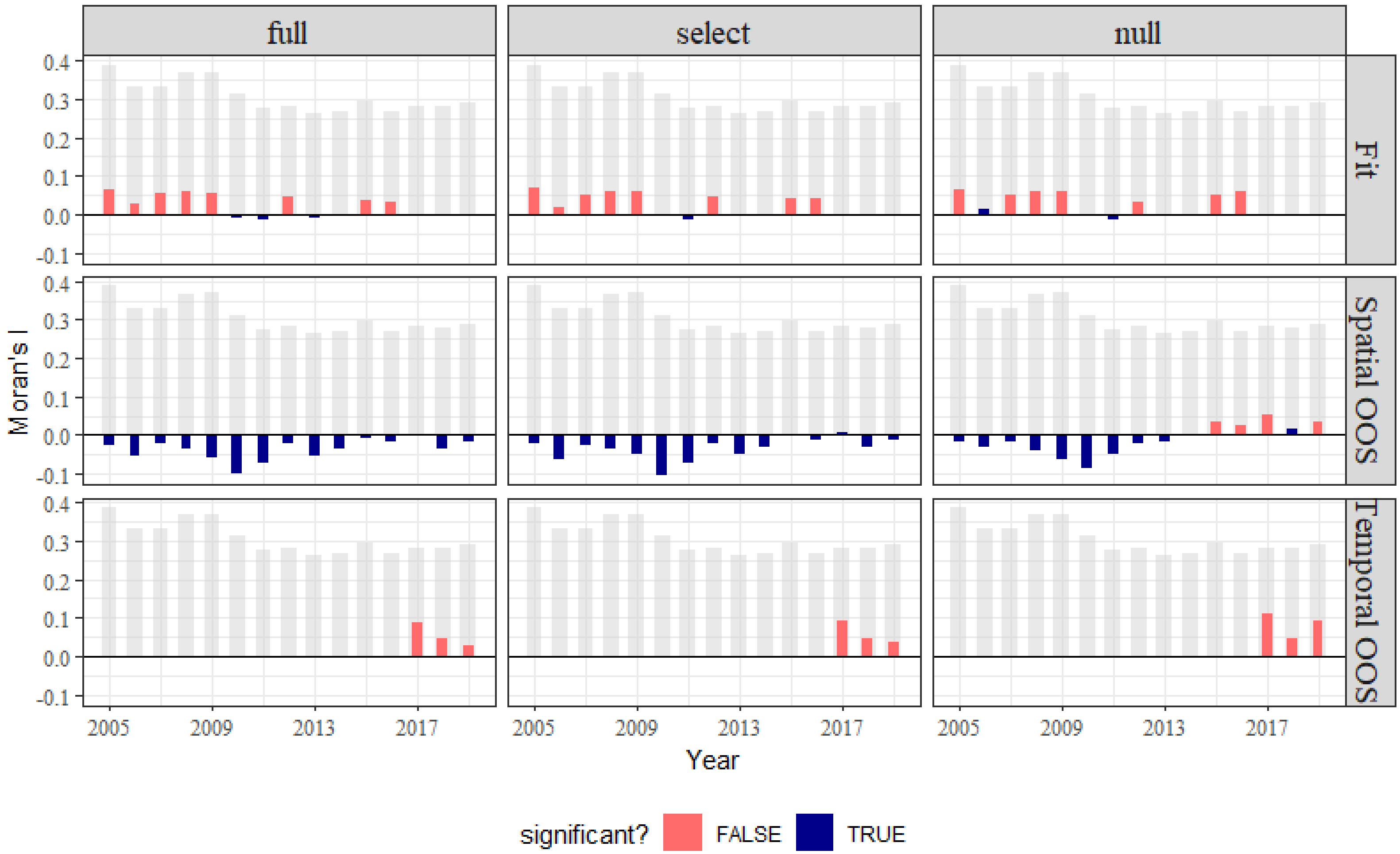
Appendix Figure 3. Mean and Median symmetric proportional error for in-sample, temporal out-of-sample and spatial out-of-sample estimates for the three CAR models, as a percent of error in *baseline*. Baseline estimates are expected deaths from population profile, μ_{ct}.



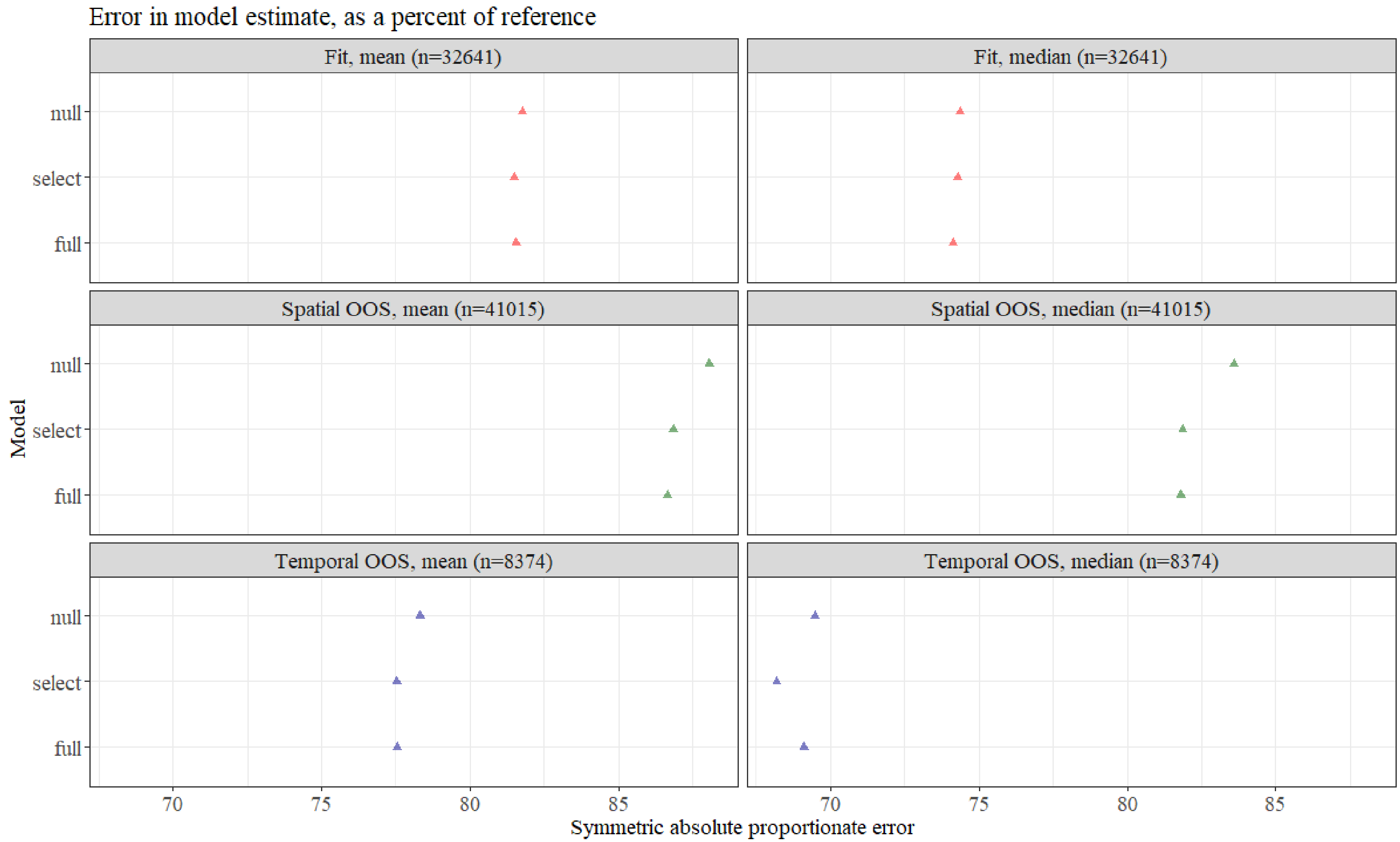
Appendix Figure 4. Trace plots for the intercept and five regression parameters in the *select* model over the fit period, for three chains (black, red, green), showing no clear trend in mean or variance, suggestive of chain convergence.



Appendix Figure 5. Scatter plot of model estimates of suicide deaths from *select* model in temporal OOS setting. Each data point represents a county. Axes are square root transformed.



Appendix Figure 6. Global Moran' I in the residual. Magnitude of Moran's I statistic is indicated by the bars, with color indicating significance. The grey bars shows corresponding Moran's I from the *baseline* model (all significant).



Appendix Figure 7. Mean and Median symmetric proportional error for in-sample, temporal out-of-sample and spatial out-of-sample estimates for all attempted model forms, as a percent of error in baseline estimates, *with zero-count county-year instances excluded*.

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