# A Spatial Analysis of the Impact of West German Television on Protest Mobilization During the East German Revolution

## Online appendix

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Contents

(1) Discussion of estimator

(2) Discussion of Irregular Terrain Model

(3) Figure 1: Counties with and without access to West German television (−85dBm cutoff level)

(4) Figure 2: Counties with and without access to West German television (−82.5dBm cutoff level)

(5) Figure 3: Counties with and without access to West German television (−80dBm cutoff level)

(6) Figure 4: Estimated propensity scores for WGTV and non-WGTV counties

(7) Figure 5: Treatment effect estimates for 100 best subsets

(8) Table I: Alternative measures of access to WGTV

(9) Additional references

As Box-Steffensmeier, De Boef, and Joyce (2007) note, repeated events processes may produce within-unit correlations in the risk of event for either of two reasons. On the one hand, there may be event dependence, so that experiencing a previous event makes a unit more (or less) likely to experience a subsequent event. Thus, for example, event dependence would exist if a previous protest in an East German county made subsequent protests in that county more likely, perhaps due to protesters' increased awareness of the East German regime's weakness. Alternatively, heterogeneity in risk propensity may make some counties more susceptible (in survival modeling terminology, more frail) to multiple protests than other counties. This would be the case, for example, if cross-county heterogeneity in deprivation made multiple protests more likely in some counties than in others, and covariates measuring this deprivation were excluded from the structural portion of the model.

In an important set of recent analyses, Box-Steffensmeier and De Boef (2006), Box-Steffensmeier, De Boef, and Joyce (2007), and Box-Steffensmeier, Linn, and Smidt (2014) compare and contrast the performance of a variety of estimators for modeling repeated events processes. The conclusion from these studies is consistent: the conditional frailty gap time model is the preferred model among available repeated events models. In examining both the bias and efficiency of five modeling approaches (the conditional frailty gap time model, the Anderson-Gill model, the conditional risk-set elapsed time model, the conditional risk-set gap time model, and the standard frailty model), Box-Steffensmeier and De Boef (2006) find that the conditional frailty gap time model performs at least as well as the alternative models in all conditions examined, and is the only model to perform well when both event dependence and unobserved heterogeneity are present. As a consequence, we employ the conditional frailty gap time model in this analysis.

The conditional frailty model is the preferred alternative because it is able to account simultaneously and directly for both event dependence and heterogeneity in repeated event processes. It accounts for the former by specifying a conditional risk set, such that unit $i$ is not at risk for experiencing the $k$th event until it has experienced the preceding $k-1$ events. Separate baseline hazards are allowed for each event by stratifying on event number. As Box-Steffensmeier, DeBoef, and Joyce (2007: 240) note, stratifying on event number accounts for event dependence, allowing for consistent coefficient estimation.

Heterogeneity is accounted for by specifying random effects, or frailty terms, for the units in the analysis. If unmodeled risk factors produce significant heterogeneity in risk propensity, the variance of the random effects will be distinguishable from zero. Thus, a probability distribution is specified for the random effects (typically either a gamma or Gaussian distribution), and the variance parameter ($\theta$) for the random effects is examined to determine whether it is distinguishable from zero. If it is, the covariates in the model do not fully capture the heterogeneity in risk propensity and the random effects are required to account for this.

The conditional frailty model can be specified in either gap time or elapsed time formulation. In the former, the time to event is the time since the unit experienced the preceding event in the repeated events process. In the latter, the time to event is the time since the unit first entered the observation period. Typically, scholars' substantive interest is in explaining the occurrence of an event since the preceding event, and as a consequence, we employ the standard gap time modeling approach for the conditional frailty models in this paper.

An important choice in modeling repeated events processes is whether to employ a parametric model such as the Weibull or the exponential, or the Cox semi-parametric alternative. The critical distinction between these two classes of alternatives is how the baseline hazard is modeled. In the parametric alternatives, the baseline hazard is assumed to follow a specific parametric distribution and is modeled by specifying this distribution. The principal advantage of a parametric model is that it provides a direct parametric estimation of duration dependence and provides for out-of-sample prediction. The critical drawback of a parametric model is that the coefficient estimates are dependent upon the choice of parametric distribution for the baseline hazard.

Alternatively, a Cox semi-parametric model may be employed. In contrast to the parametric alternatives, the Cox model does not specify a parametric distribution for the baseline hazard. As a consequence, the baseline hazard is not directly modeled, although an empirical baseline hazard may be recovered post estimation. The advantage of the Cox model is that it is much more flexible than its parametric counterparts and is not susceptible to erroneous inferences that may arise regarding the effects of substantive predictors as a consequence of misspecifying the underlying baseline hazard. A disadvantage of the Cox model is the absence of a (correctly chosen!) parametric model of the baseline hazard and corresponding out-of-sample predictions. In our application, we

are not interested in out-of-sample prediction. Given this, we employ the much more flexible Cox semi-parametric modeling approach.

The hazard in our conditional frailty gap time model takes the form

$$\lambda_{ik}(t) = \lambda_{0k}(t - t_{k-1})e^{X_{ik}\beta+\omega_i}, \tag{1}$$

with $k$ denoting the event number, $\lambda_{0k}$ a baseline hazard rate that varies by event number (i.e., event strata), $(t-t_{k-1})$ denoting the gap time formulation with the hazard being the risk for event $k$ occurring since the occurrence of the $(k-1)$th event, $X$ denoting the matrix of predictors including the WGTV treatment indicator, $\beta$ denoting the coefficients to be estimated, and $\omega_i$ denoting the unit-specific frailties that are assumed to be constant over time for each unit but may vary across units (Box-Steffensmeier, De Boef and Joyce 2007: 242).

The partial likelihood, conditional on the frailty terms, is then

$$L(\beta) = \prod_{i=1}^{n}\prod_{k=1}^{K}\left(\frac{e^{X_{ik}\beta+\omega_i}}{\sum_{i=1}^{n}\sum_{k=1}^{K} Y_{ik}e^{X_{ik}\beta+\omega_i}}\right)^{\delta_{ik}}, \tag{2}$$

where again, $k$ refers to the event number or stratum, $\delta$ is a censoring indicator that equals 1 if the unit is observed and 0 if the unit is censored, and $Y_{ik}$ is an at-risk indicator that is equal to 1 if unit $i$ is at risk of experiencing event $k$ and 0 otherwise (Box-Steffensmeier, De Boef, and Joyce 2007: 242).

The conditional frailty gap time model introduced by Box-Steffensmeier and De Boef (2006) is a critical advance in estimation for repeated events models. Simultaneous to this advance in repeated events modeling, scholars have also been making advances in modeling spatial dependence in event processes. Here, scholars are interested in examining whether risk propensity among the neighbors of unit $i$ affects the risk of unit $i$ experiencing the event of interest. These advances are reflected in, among others, Banerjee, Carlin, and Gelfand (2004) and Darmofal (2009). To date, however, these advances in repeated events modeling and spatial modeling have occurred along separate tracks. To the best of our knowledge, this is the first analysis that simultaneously accounts for spatial dependence, event dependence, and heterogeneity within a repeated events framework. It does so through a spatial conditional frailty gap time modeling framework.

We extend the conditional frailty model to include spatial dependence through the inclusion of a conditional spatial lag predictor variable. Specifically, we include a temporally lagged spatial lag

variable that measures the proportion of county $i$'s neighbors that experienced a protest event on the preceding day, during the preceding week, or during the preceding 2 weeks. Thus, we allow for neighboring counties' recent protests to affect the probability of county $i$ experiencing a protest event, conditional on covariates, access to WGTV, and the frailty terms.

Survey data as well as detailed WGTV signal strength measurements on the ground confirm that people living in the city of Dresden could not watch WGTV in 1989 (see Kern & Hainmueller 2009). Since we do not know the technical characteristics of the various television receivers in use throughout East Germany, we use the modeled average signal strength in the center of Dresden (−86.5 dBm) as the cutoff for access to WGTV. Note that this is a conservative measure of access to WGTV since WGTV availability in the city of Dresden was very poor. In other words, we are very confident that counties with modeled signal strength below this threshold did *not* have access to WGTV. As a robustness check, we also use three other cutoff values, −85dBm, −82.5dBm, and −80dBm, representing increasingly stricter standards for considering a county to have access to WGTV. Our results are entirely robust to using these alternative measures of WGTV availability (see Table I below).

In what follows we describe both the software and the process used to create our WGTV treatment variable based on an electromagnetic signal propagation model. We used ArcGIS Desktop 9.3 in conjunction with the Communication System Planning Tool (CSPT) extension for ArcGIS, created by the Institute for Telecommunication Sciences at the US Department of Commerce for the US Department of Defense. CSPT provides a set of functions for modeling the spatial propagation of electromagnetic signals based on terrain data in conjunction with information about the characteristics of broadcast transmitters and radio receivers. Similar commercial software is used by mobile phone providers, for example, to create coverage maps of their services.

We modeled the geographic coverage of all main ARD and ZDF broadcast transmitters (*Grundnetzsender*) with a power of at least 100 kW. Broadcast transmitter data were taken from Norddeutscher Rundfunk (1989), which lists the power, frequency, and polarization of all West German broadcast transmitters in operation at the beginning of 1989. Data on broadcast transmitter latitude, longitude, altitude, and height are from Wikipedia; all latitudes and longitudes were confirmed using Google Maps' Satellite View. We were able to include 120 out of 124 existing main broadcast transmitters. The remaining 4 transmitters had to be omitted due to missing data on antenna height, an important variable in radio signal reception. We uniformly set the radio receiver height to 10 meters above ground, following common practice (DeBolt n.d.).

The CSPT extension uses the Longley-Rice Model (also known as the Irregular Terrain Model).

This model 'predicts the median attenuation of a radio signal as a function of distance and the variability of the signal in time and in space' (DeBolt n.d.: 76). Since its development in 1968, the Longley-Rice model has been regularly used to model the effect of topography on radio signal reception (DeBolt n.d.; Longley and Rice 1968; National Institute of Standards and Technology 2004: 36; National Telecommunications and Information Association n.d.; Seybold 2005: 143). The Longley-Rice model can account for a number of site characteristics such as climate zone type and ground conductivity (DeBolt n.d.; Longley and Rice 1968). We kept the majority of these characteristics at their default values (DeBolt n.d.) since they either do not affect coverage area predictions or do not apply to our specific model. We used the 'Single/Multiple Transmitter Coverages' function of CSPT, which 'run[s] propagation analyses on each transmitter individually and then combine[s] these individual coverages into a single composite coverage of all the transmitters in the scenario' (DeBolt n.d.: 60). This procedure generated a coverage map displaying modeled available power for 1 km $\times$ 1 km cells covering all of East Germany. Modeled available power ranges from 8.97dBm to $-117$dBm. However, we are not primarily interested in variation in this continuous measure of WGTV signal strength across East German counties. More important for our purposes is a binary measure: could the residents of an East German county receive WGTV broadcasts in acceptable quality? Survey data as well as detailed WGTV signal strength measurements on the ground confirm that people living in Dresden could not watch WGTV in 1989 (see Kern and Hainmueller 2009). Since we do not know the technical characteristics of the various television receivers in use throughout East Germany, we use the modeled average power in the center of the city of Dresden ($-86.5$ dBm) as the cutoff for access to WGTV.[1] Consequently, East German counties that have a modeled average WGTV signal strength below $-86.5$dBm are coded as not having access to WGTV; all other counties are coded as having access to WGTV. We code counties as receiving signal above the cutoff if more than 50% of a county's area receives signal equal to or greater than the cutoff value. As a robustness check, we also use three other cutoff values, $-85$dBm, $-82.5$dBm, and $-80$dBm, representing increasingly stricter cutoffs for considering a county to have WGTV. Maps showing WGTV and non-WGTV counties based on these cutoffs are included in this online appendix (Figures 1, 2, and 3). Moreover, in our robustness analysis we

[1]The same approach has been used in previous research (DellaVigna et al. 2014).

also present results for the fraction of each counties' area that receives signal above one of the four cutoff values.

Table I evaluates the sensitivity of our results to alternative measures of WGTV availability. Specifications 1–3 in Table I use increasingly strict cutoff values for coding a county as having WGTV. Specifications 4–7 use these same cutoffs, but now we use the fraction of a county's area that is above the respective cutoff level as a measure of access to WGTV. Finally, specification 8 uses Kern's (2011) WGTV coding. Across all specifications, the effect of WGTV is small (positive or negative) and far from statistical significance.

Figure 1: East German counties with and without access to West German television based on Longley-Rice radio signal propagation model and cutoff level of −85dBm

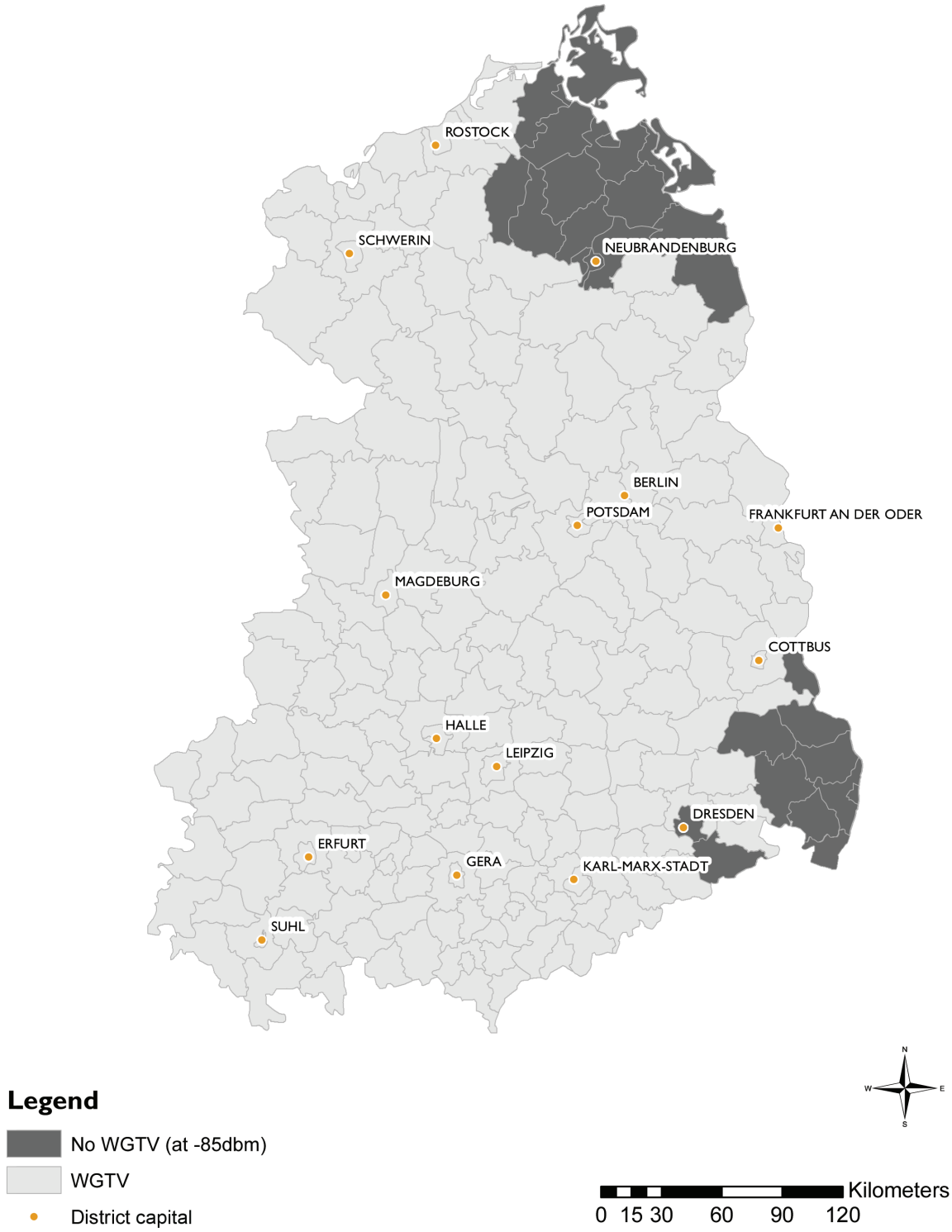


Figure 2: East German counties with and without access to West German television based on Longley-Rice radio signal propagation model and cutoff level of −82.5dBm

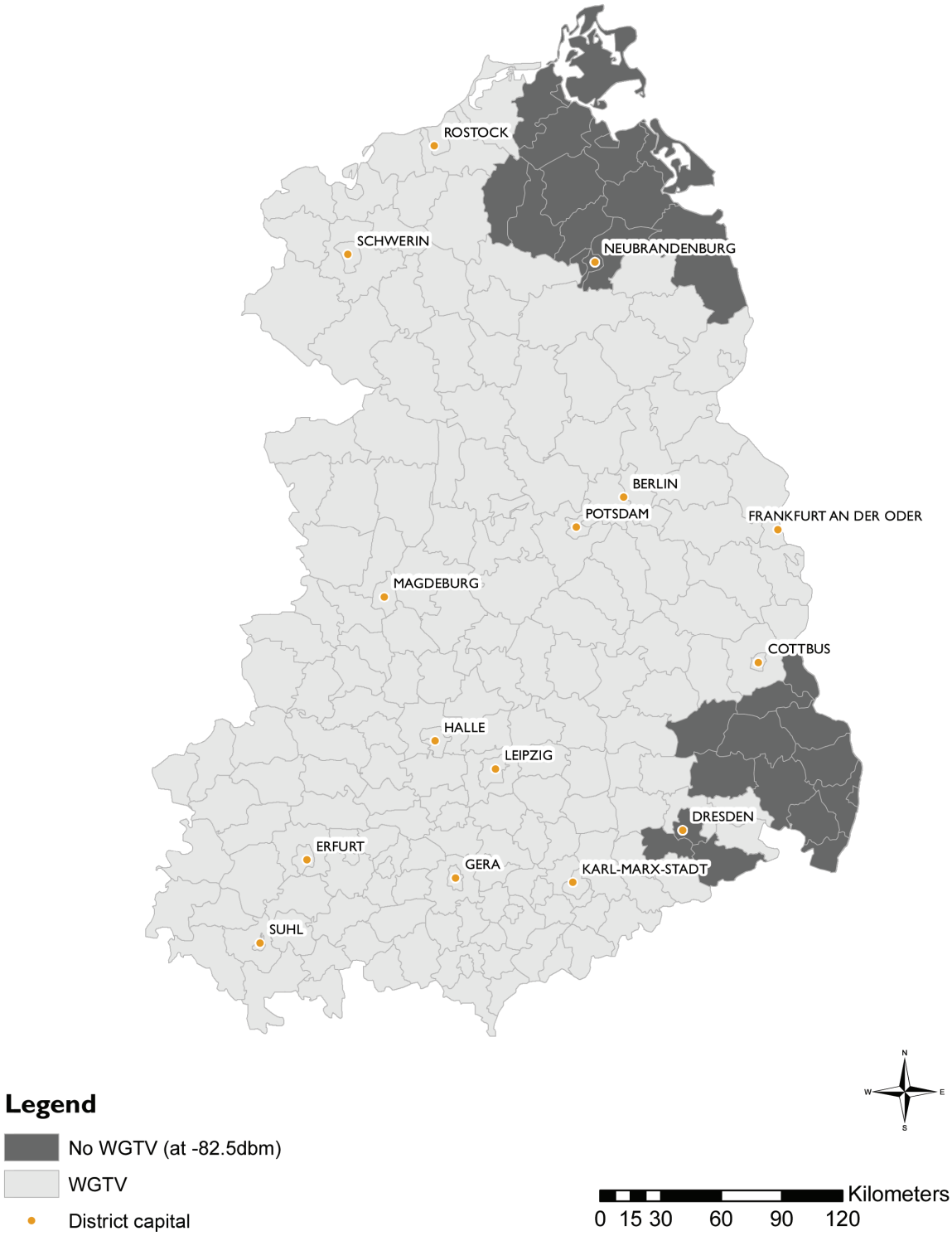


Figure 3: East German counties with and without access to West German television based on Longley-Rice radio signal propagation model and cutoff level of −80dBm

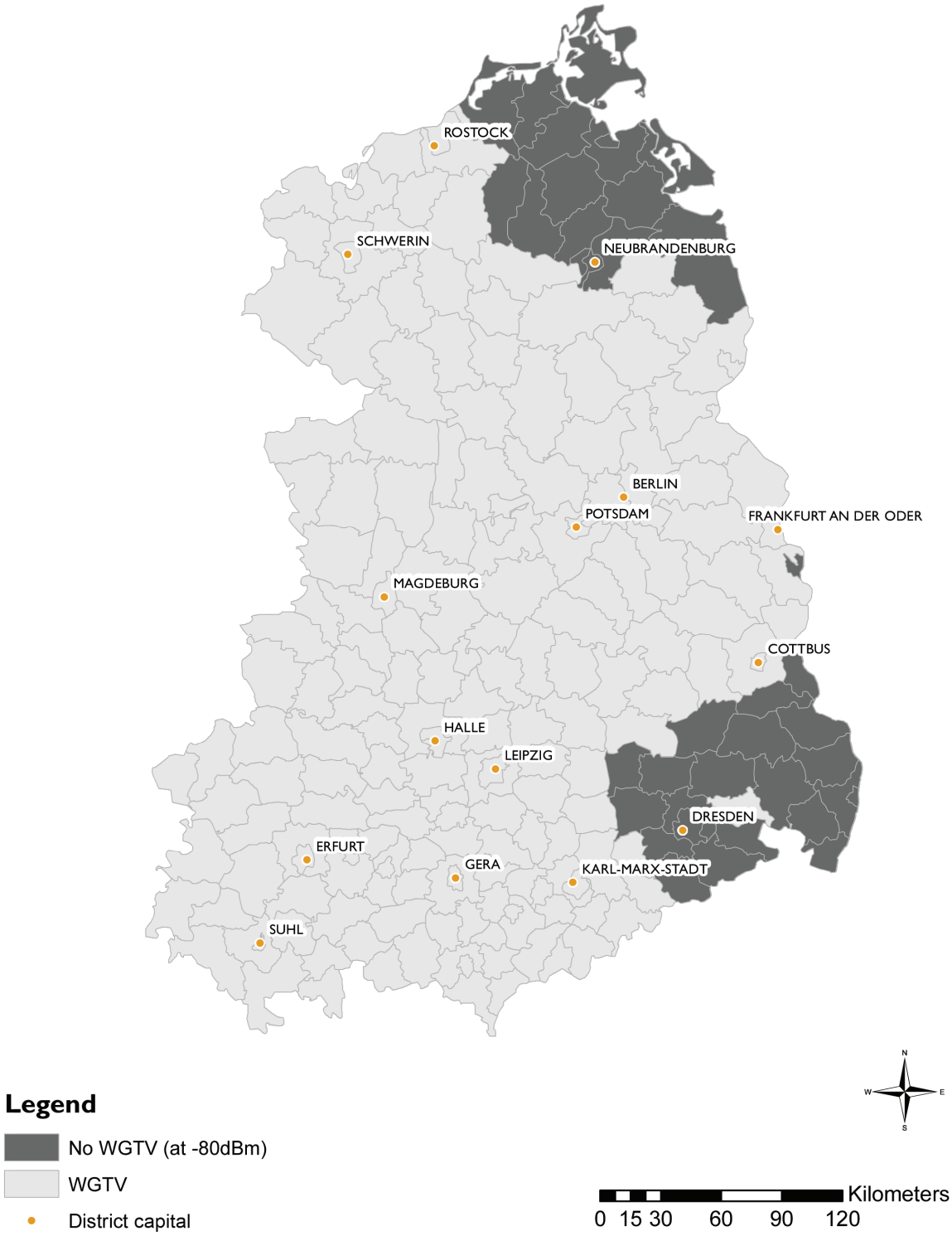
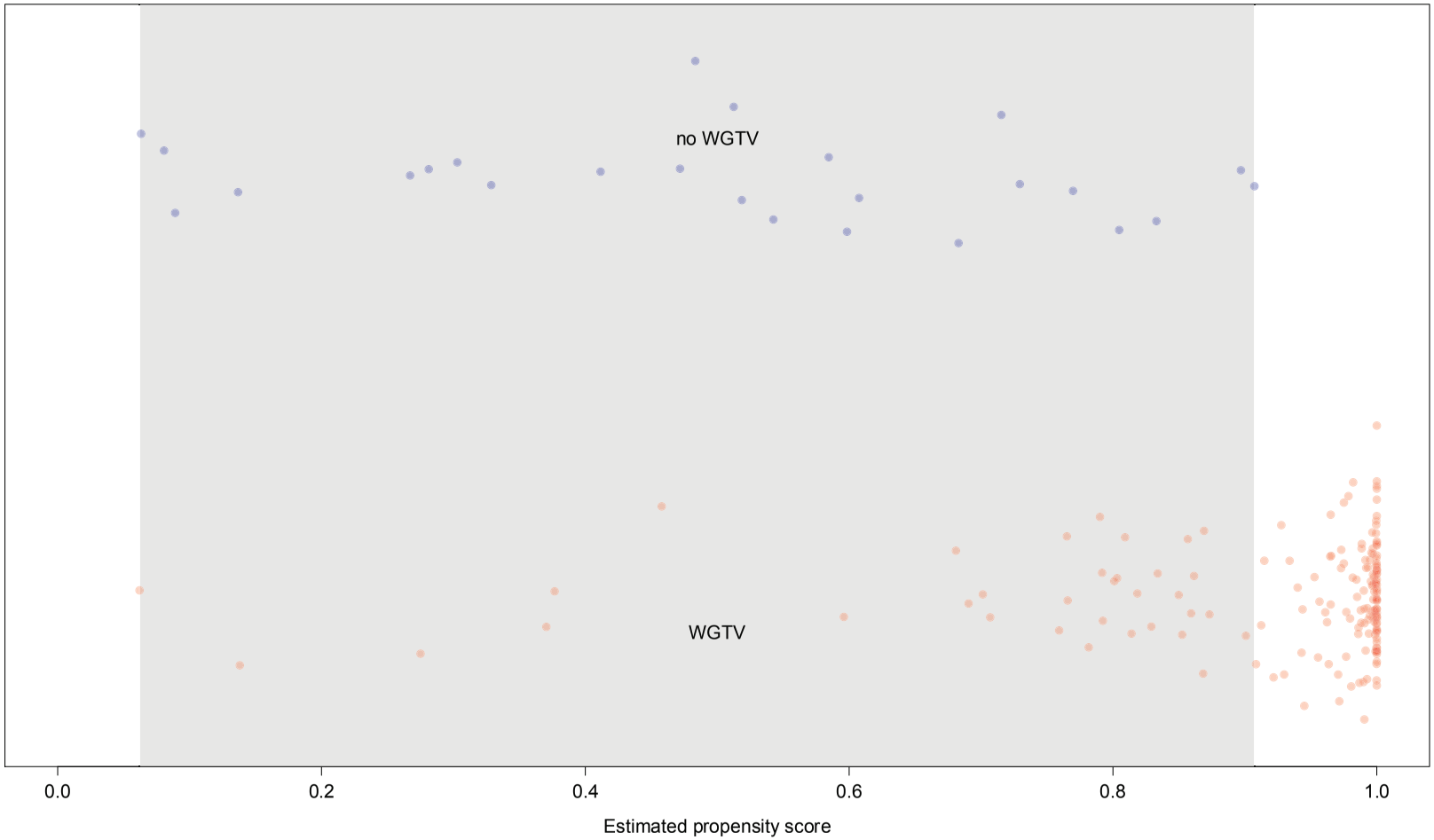
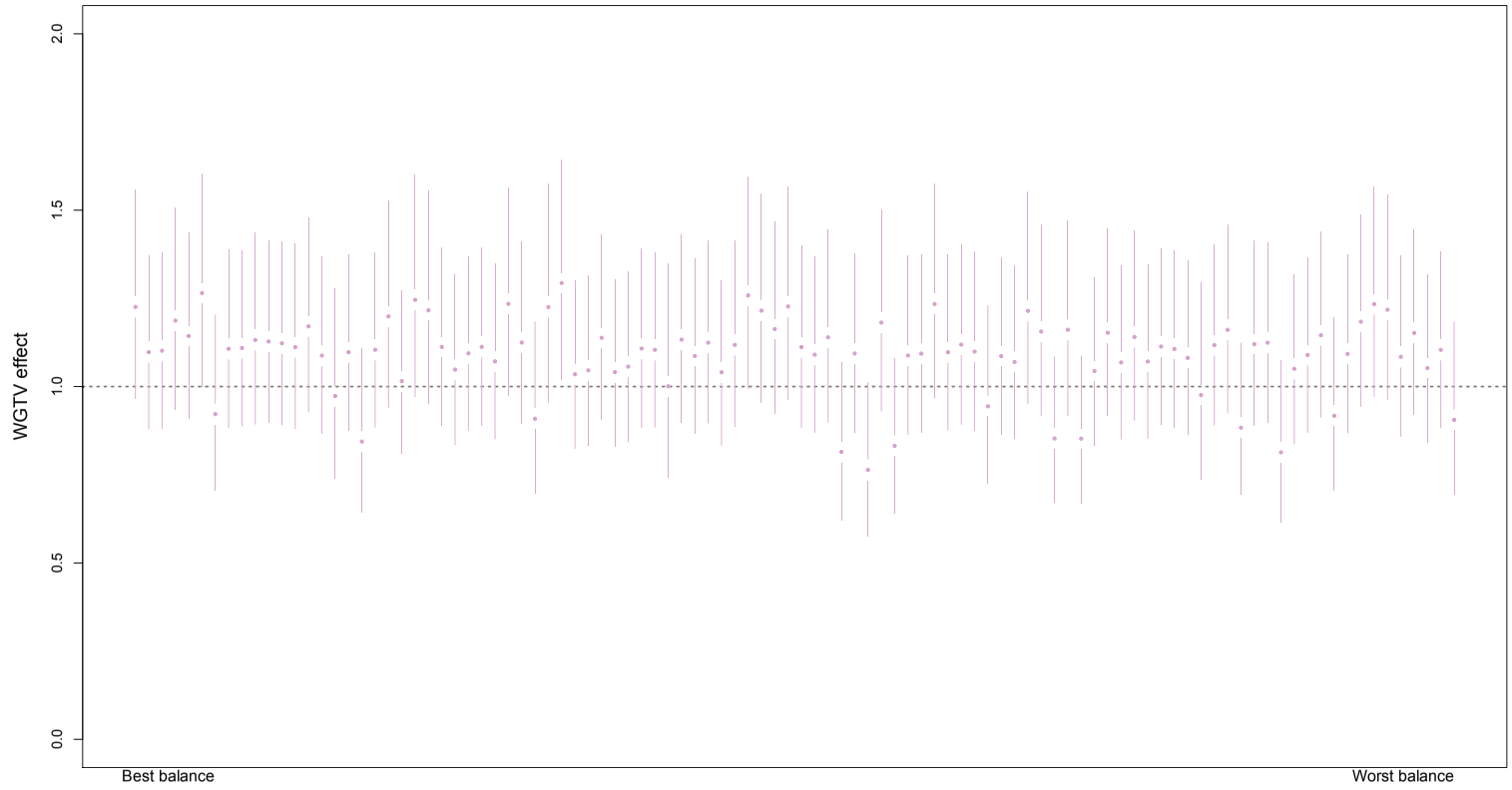


Figure 4: Estimated propensity scores for WGTV and non-WGTV counties




The figure shows estimated propensity scores, jittered vertically, for WGTV (red) and non-WGTV (blue) counties. The area of overlap is shown in grey. 125 WGTV counties have estimated propensity scores in excess of .95.

Figure 5: Causal effect estimates for WGTV from baseline Cox model for 100 best subsets.




Estimates and 95% confidence intervals are shown. Estimates are sorted in decreasing balance as measured by the average absolute standardized difference in means across all 24 covariates

Table I: Effect of WGTV on probability of protest event from Cox models: Alternative measures of access to WGTV

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| WGTV (−85.0dBm) | 0.093 | | | | | | | |
| | [0.171] | | | | | | | |
| WGTV (−82.5dBm) | | 0.028 | | | | | | |
| | | [0.169] | | | | | | |
| WGTV (−80.0dBm) | | | −0.060 | | | | | |
| | | | [0.157] | | | | | |
| % WGTV (Dresden) | | | | 0.131 | | | | |
| | | | | [0.226] | | | | |
| % WGTV (−85.0dBm) | | | | | 0.098 | | | |
| | | | | | [0.211] | | | |
| % WGTV (−82.5dBm) | | | | | | 0.034 | | |
| | | | | | | [0.197] | | |
| % WGTV (−80.0dBm) | | | | | | | −0.013 | |
| | | | | | | | [0.185] | |
| Kern (2011) WGTV | | | | | | | | −0.033 |
| | | | | | | | | [0.193] |
| Covariates | yes | yes | yes | yes | yes | yes | yes | yes |
| Frailties | yes | yes | yes | yes | yes | yes | yes | yes |
| Number of events | 2,598 | 2,598 | 2,598 | 2,598 | 2,598 | 2,598 | 2,598 | 2,598 |
| Number of observations | 40,365 | 40,365 | 40,365 | 40,365 | 40,365 | 40,365 | 40,365 | 40,365 |
| I-likelihood | −8,741 | −8,741 | −8,741 | −8,741 | −8,741 | −8,741 | −8,741 | −8,741 |

The table shows coefficient estimates from eight Cox model specifications, with standard errors in brackets.
† significant at 10 percent level.
* significant at 5 percent level.
** significant at 1 percent level.

DeBolt, Robert. n.d. *Communication system planning tool: Full menu toolbar user guide.* Boulder, CO: Institute for Telecommunication Sciences.

Longley, Anita G. and Philip L. Rice. 1968. "Prediction of tropospheric radio transmission loss over irregular terrain: A computer method." Boulder: Institute for Telecommunication Sciences.

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Seybold, John S. 2005. *Introduction to RF propagation.* Hoboken: John Wiley & Sons.