# Online Supplement

## Statistical Methods

The ESSENCE dataset included data for 369 out of the 677 zip codes in our study area. Because a limited number of Houston EDs contributed to the dataset, this gap likely indicates that some patients were not represented in the ESSENCE records and, therefore, the true number of patients from these zip codes was not zero. To correct for this, we used a geostatistical interpolation method called Empirical Bayesian Kriging.1 The algorithm took PSTAY values as inputs, applied normal score transformation, estimated the values for the ZCTAs with no data, and back-transformed the results. This produced a dataset with PSTAY values for each ZCTA in our study area for both the short-term and long-term timeframes (see Figure S1). We used global Moran’s I tests to detect spatial autocorrelation in these values and to identify the presence of significant clusters or “hot spots.”

In order to assess the relationship between the location at which patients presented for care and the explanatory variables, we built three regression models using the R programming package. Model 1 included the four CDC SVI themes as the explanatory variables. Model 2 retained the four themes and added population density. Model 3 retained the explanatory variables from Model 2 and added flood inundation. For each of these models, we assessed the best specification based on diagnostics to assess spatial dependence and its form. We fit ordinary least-squares (OLS) regression with PSTAY as the dependent variable regressed on the explanatory variables. Diagnostic tests from these regressions were used to identify spatial dependence (Moran’s I test of regression residuals) and to select the appropriate type of spatial regression specification to use (LaGrange Multiplier tests and Robust LaGrange Multiplier tests). Based on these diagnostics, we built the final three spatial lag models using the same set of explanatory variables. The best performing model of the three was chosen based on log likelihood and Akaike Information Criteria (AIC).

The EBK introduced additional uncertainty into our spatial regression estimates. We sought to test the sensitivity of these estimates to the uncertainty introduced via kriging by including the standard error of the kriged PSTAY observations as an additional variable in the spatial regressions. While inelegant, this approach did allow for the influence that the kriged error had on the outcome variable directly as well as through the covariates.

## Results

The results of EBK are shown in Figure S1; in the pre-EBK map, many ZCTAs have no data, while in the post-EBK map, those gaps have been filled with estimated values. Table S1 presents parameter estimates and diagnostics for the three models for each of the time periods. With neighbors defined based on queen contiguity, Moran’s I indicated spatially autocorrelated residuals for each model. This suggested that a model designed to explicitly take spatial dependence into account could achieve better results. We used Lagrange Multiplier test statistics2,3 to determine that a spatial lag model would be an appropriate choice.

Because LaGrange Multiplier tests were significant for both the error and lag models, we considered the robust LaGrange Multiplier (RLM) tests, which are robust to the presence of the other type of spatial autocorrelation. The insignificant RLM for the error model coupled with the strongly significant RLM for the lag model indicates the spatial lag model is the preferred approach to modeling spatial dependence in each model for both the short and long time periods. Finally, the smallest Akaike Information Criterion and the largest log likelihood for the lag model indicated that the best model in the short and long time periods is Model 3. Diagnostics from Model 3 in both the STP and LTP revealed remaining residual autocorrelation, indicating some spatial dependence remains to be explained after controlling for the explanatory variables and including the spatial lag.

 As Table S1 presents, in each model and both time periods, the estimated coefficient on the spatial lag was positive, indicating that if a neighboring ZCTA had high PSTAY the ZCTA observed also tended to have high PSTAY. Increased socioeconomic vulnerability was associated with increased PSTAY. Increases in housing composition and disability vulnerability were associated with declined PSTAY. Themes 3 and 4 were not significantly associated with PSTAY. While population density was positively associated with PSTAY, the magnitude of the effect was very small. Increased flooding inundation was also positively associated with PSTAY. Note that the standard error from EBK was significant in the STP but not significant in LTP. However, while significant, the effect was very small even in STP and entered principally through increased error. Nonetheless, impact results that reflect adjustment for the standard error from EBK are presented in Table S2.

 Figure S2 demonstrates the improved performance of the spatial lag regression as compared with the OLS regression. Residuals for the OLS model (left) are higher, exhibiting strong spatial autocorrelation. This is visible in the clusters of high values on the map and is confirmed by diagnostic tests. Residuals for the spatial lag model (right) are lower overall and show reduced clustering. However, some residual spatial autocorrelation is still present.

## References

1. Krivoruchko K. Emprical Bayesian Kriging Implemented in ArcGIS Geostatistical Analyst. *ArcUser*. 2012;3: 6-10. <https://www.esri.com/NEWS/ARCUSER/1012/files/ebk.pdf>. Accessed November 19, 2019.
2. Anselin L. Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity. *Geographical Analysis*. 1988;20(1):2-17. doi: 10.1111/j.1538-4632.1988.tb00159.x.
3. Anselin L, Rey S. Properties of Tests for Spatial Dependence in Linear Regression Models. *Geographical Analysis*. 1991;23(2):112-131. doi: https://doi.org/10.1111/j.1538-4632.1991.tb00228.x.