Ring Around the Neighborhood: Spatial Analysis of Doorbell Camera Use

_Surveillance, Spatial Analysis, Policing_

**Extended Abstract**

The surveillance of public and private spaces has become a private market in the U.S., with companies such as Amazon performing surveillance as part of both internal business practices and consumer products [1]. New direct-to-consumer surveillance products like the Ring doorbell camera are marketed as personal and community security devices, but little is known about the breadth and extent of their use. As of February 2020, Ring is in active partnership with 887 law enforcement agencies across the U.S., making understanding their spread an urgent matter for privacy and civil liberty advocates nationwide [2, 3, 4]. We use data collected from the Ring Neighbors app to create what we believe to be the first comprehensive map and analysis of doorbell camera use across the continental U.S. We aggregate this map to the county level, and use spatial auto-regressive modeling to explain Ring Neighbors app usage as a function of county demography and crime reporting data.

We model the number of cameras in each U.S. county that posted to the Ring Neighbors social network app since 2017 using demographics from the 2012-2015 U.S. ACS and FBI UCR crime statistics as explanatory variables [5]. For each county, we regress on its racial composition, median household income, homeownership rate, median home value, and crime reporting rates, including motor vehicle theft, property theft, robbery, assault, and total violent crime. We also include fixed effects for each state, and control for the total population and land area of each county.

Our variables exhibit spatial dependence: A Moran’s $I$ of 0.11 and $p = 3 \times 10^{-10}$ indicate correlation between neighboring counties. To correct for spatial bias, we adopt a spatial regression model. An LM test indicates a spatial autoregressive lag model (SARLM) fits our data best, so we report _total impact_ estimates from a fitted SARLM model instead of traditional coefficient estimates. Total impact is measured by measuring the effect of simulated changes in predictor variables on a county’s outcome as well as the outcome of neighboring counties.

Figure 1: County density map of Ring cameras that posted to the Ring Neighbors app since 2017.
Figure 2: Total (direct + indirect) impact of county-level variables on number of active Ring cameras, corrected for spatial autocorrelation and estimated using a spatial simultaneous autoregressive model. Impacts are calculated through 500 MCMC draws. Model has a pseudo R squared of 0.79. Bars represent standard errors for impact estimates.

Figure 2 shows the total impact estimates of our dependent variables on the number of active Ring cameras in a county. Given the amount of race-based rhetoric and critique surrounding the platform and its use [6], it is surprising that no racial variables show a significant impact. The results suggest that less expensive, middle-income neighborhoods with comparatively low home values are more likely to use the Ring platform. Ring is often discussed as an anti-package theft mechanism, but “theft”, which includes package and other property theft, does not show a significant impact. Other property crime, such as robbery and vehicle theft, instead carry the highest impact, with a unit increase in vehicle theft corresponding to 13% more Ring cameras in a county. Counties with higher rates of violent crime, meanwhile, tend to have fewer cameras. The Ring platform appears to be mainly associated with property crime and access.

With 39% of counties in the U.S. having at least one Ring camera that has posted a video since 2017, and an average of 1462 Ring “alerts” posted every day in the continental U.S. since July 2019, this work provides a crucial first step into understanding how and why this popular technology is spreading across the U.S.

References


