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Searching for safety: crime prevention in the era of Google

Megan S. Stubbs-Richardson*, Austin K. Cosby, Karissa D. Bergene and Arthur G. Cosby

Abstract

This research investigated the association between Internet searches and property crime levels in the United States. States with the highest levels of property crime tended to have the highest levels of Google crime prevention queries for target hardening, surveillance, and formal and informal social control. In addition, levels of crime reduction were often greatest in states with more crime prevention queries and the magnitude of the reduction was often substantial. Findings from this research support the conceptualization of aggregated online crime prevention queries as a potential factor for understanding crime reduction strategies and overall changes in crime rate patterns at the state-level.

Keywords: Property crime, Internet searches, Google, Crime prevention, Target hardening, Surveillance, Social control, Google Correlate, Motor vehicle theft, Burglary

Introduction

The purpose of this study is to assess whether and how people use Google to prevent crime. Individuals may use Google searches to learn about an array of topics, including crime and its prevention. For instance, Google searches may be used to research products online, such as deadbolts, security doors, or alarm systems. Such crime prevention efforts can decrease offender motivation, decrease target suitability, and increase capable guardianship (Cohen and Felson 1979; Wilcox and Cullen 2018). Google may also be used to seek information about law enforcement and community efforts related to crime prevention such as how to file a police report or organize a neighborhood watch.

In this study, Google searches are examined at the aggregate state-level for the following queries: (1) target hardening, (2) surveillance, (3) formal social control, and (4) informal social control. Target hardening prevents crime by decreasing access to property. Installing deadbolts, locks, or security doors are examples of target hardening. Surveillance includes formal and natural efforts to increase risks in offender decision-making. Formal surveillance uses technological security to deter crime, whereas natural surveillance involves changes to the environment. Examples of surveillance include Closed Circuit Television Camera (CCTV) and street lighting. Formal social control involves the use of organizations, such as police, to deter offending behavior. Examples include contacting or reporting crime to the police. Informal social control involves the use of organizations and networks of people to deter offenders using rewards and punishments associated with norms. Neighborhood watch programs are examples of informal social control.

To our knowledge, this is one of only three studies (Gamma et al. 2016; Gross and Mann 2017) to utilize Google search data with crime data to investigate a traditional crime research topic. This study is the first to investigate the association between Google crime prevention searches and property crime rates. We seek to answer three questions in this study: (1) Are higher rates for property crime associated with searches for crime prevention information?; (2) Are increased levels of crime prevention searches associated with reductions in property crime?; and (3) If there is a reduction, what is the magnitude of that reduction? To answer these research questions, we merged Federal Bureau of Investigation (FBI) Uniform Crime Report (UCR) data with

*Correspondence: megan@ssrc.msstate.edu
Social Science Research Center, Mississippi State University, P.O. Box 5287, Mississippi State, MS 39762, USA

Google Correlate data for predetermined crime prevention queries.

Background

In 2018, 89% of United States (U.S.) adults reported using the Internet (Pew Research Center 2018). U.S. Internet users tended to be college educated, between the ages of 18 and 49 and had an annual income over $30,000. Individuals in urban and suburban areas were more likely to be Internet users (Pew Research Center 2018). U.S. rates of Internet usage are similar for White, Black, and Hispanic men and women (Pew Research Center 2018). Search engine optimization and increased Internet access has led to the pervasiveness of online searches for information acquisition. According to Purcell et al. (2012), 91% of all online adults use search engines. Of those using search engines, roughly 83% rely on Google (Purcell et al. 2012).

Google users can search for subjects, such as pornography or personal health concerns, that they may wish to keep private. Thus, a strength of Google search data is that it allows researchers to access data about controversial or sensitive topics that might not be as readily obtained in traditional methodologies such as survey research (Stephens-Davidowitz 2014). To date, researchers have analyzed Internet query data for a variety of topics, including: difficult to survey populations (Chykina and Crabtree 2018), social movements (Gross and Mann 2017), political behavior (Ma-Kellams et al. 2017; Stephens-Davidowitz 2014), health-seeking behavior (Nuti et al. 2014; Telfer and Obradovich 2017; Zhang et al. 2018), consumer behavior (Goel et al. 2010), weather and disaster related concerns (Sherman-Morris et al. 2011), suicide surveillance (Ayers et al. 2017; Gunn and Lester 2013; Hagihara et al. 2012; Ma-Kellams et al. 2016; Sueki 2011), AIDS (Mavragani and Ochoa 2018), pornography (Makin and Morczek 2015; Whitehead and Perry 2018), and illicit drug use (Gamma et al. 2016). Internet searches provide an innovative way to learn about crime prevention. In this study, we apply crime theories from environmental and community perspectives to assess Internet query associations with property crime rates.

Literature review

Crime trends and the security hypothesis

In Western, industrialized nations, property crime has largely declined since the early 1990s (Baumer et al. 2018; Berg et al. 2016; Farrell 2013; Lauritsen et al. 2016; Tonry 2014; Truman and Rand 2011). Using the National Crime Victimization Survey and the International Crime Victim Survey to empirically examine seventeen competing theoretical perspectives on the international crime drop, Farrell et al. (2013, 2014) found support for the security hypothesis. The security hypothesis states that with increased and improved technological surveillance, criminal opportunities are restricted. This in turn explains the decline in property crimes. Thus, security served as an efficient type of crime prevention for restricting criminals from committing property crimes, such as motor vehicle theft, larceny theft, and burglary (Farrell 2013; Tilley et al. 2015; Tseloni et al. 2017; van Dijk et al. 2012).

Situational opportunity and community theories of crime

Property crimes are driven by offenders' perception of criminal opportunity. Their perception is flavored by factors such as the accessibility of suitable targets, associated risk and rewards (Clarke 2012; Felson and Clarke 1998), and absence of capable guardians (Clarke 2012; Cohen and Felson 1979; Reynald 2015). Crime is likely to occur when motivated offenders and suitable targets converge in space and time where there is a lack of guardianship (Cohen and Felson 1979). Community crime rates are often explained by community-level factors like socioeconomic disadvantage, residential turnover, and social and physical disorder based on Social Disorganization Theory and Broken Windows Theory (Miethe and McDowall 1993; Sampson and Groves 1989; Sampson et al. 1997; Shaw and McKay 1942; Wilson and Kelling 1982).

Literature from Environmental Criminology and Community Criminology have been successfully integrated via a multi-level opportunity framework, finding both individual and community variables to explain burglary victimization (Miethe and McDowall 1993; Wilcox et al. 2007). Miethe and McDowall (1993) found individual-level guardianship efforts to be more difficult to implement in socially disorganized areas and suggested that more extensive programs should be targeted to those areas.

Miethe and McDowall (1993) work was later advanced by Wilcox et al. (2003) multi-contextual criminal opportunity theory which specifies how opportunity structures both affect and interact at the individual and environmental level. As aggregate guardianship increases, neighbors are more likely to engage in crime prevention efforts (Wilcox et al. 2007).

Crime prevention strategies

Although there are many crime reduction strategies (e.g., policing, courts, and corrections) that focus on the individual, this study relies primarily on ecological concepts derived from (1) situational crime prevention (SCP) and (2) community crime prevention (CCP). These emphasize the context of place or situations in which crime is more likely to occur. SCP is a place-based crime prevention strategy that seeks to reduce criminal opportunities by altering conditions that make offending riskier, more

difficult, and less rewarding to motivated offenders. Target hardening and surveillance are examples of SCP, but SCP can include formal and informal social control (Wilcox and Cullen 2018).

Target hardening is limiting or restricting access to desirable targets (e.g., installing doors and/or window locks). These measures reduce the suitability of targets and thus criminal opportunities (Reynald 2015). Target hardening reduces crime particularly when individual efforts are combined with informal social control (Miethe and McDowall 1993).

Surveillance involves the alteration of the physical or natural design of places to make areas more visible and the implementation of technological security. Jacobs (1961) and Newman (1972) were among the first to highlight the importance of natural surveillance through environmental design and alteration of physical aspects of places, for example, via improved lighting. Surveillance also includes formal measures such as improved security through alarm systems or motion detection cameras. Surveillance has been found to explain reductions in burglary across the U.S., Wales, and England (Miethe and McDowall 1993; Tseloni et al. 2004).

CCP is the use of rewards or punishments to ensure that individuals obey group norms (e.g., respect for others and property) to improve safety and well-being of communities. Formal and informal social control are examples of CCP, but CCP efforts can also include target hardening or surveillance efforts in prevention (Wilcox and Cullen 2018).

Formal social control involves using institutions, such as law, police, and corrections, to prevent crime. Informal social control relies on rewards and punishments associated with norms to be enacted by residents to deter offenders. Carr (2003) suggested the need for a convergence of formal and informal social control efforts to effectively prevent crime. Carr (2003) argued that by creating government programs to fund local participation acts, such as volunteer community organizations, residents will begin to improve trust of neighbors and government organizations. Complementing formal with informal social control efforts tends to be effective in achieving public order (Weisburd et al. 2014) and reducing crime (Carr 2012; Ramey and Shrider 2014).

Crime is higher in areas characterized by social and physical disorder, which in turn, heightens fear of crime and legal cynicism; this reduces the likelihood that individuals will engage in formal or informal social control (Reynald 2015; Sampson and Wilson 1995). However, studies that compared data from socially disorganized places found that locations with increased place managers tend to have lower crime rates (Eck 2002). Further, areas with greater trust and willingness to intervene, a concept known as collective efficacy, also tend to produce lower crime rates (Sampson et al. 1997; Sampson 2011).

Engagement with social control may vary based on access to technology related networks (Sampson 2011), such as the Google search engine. Sampson (2011) argued that technology-mediated efficacy may increase collective efficacy. Sampson (2011) suggested that, in addition to the network component needed for informal social control, technology may also serve as a resource to "knit together weak community ties for the purposes of building collective efficacy" (Sampson 2011, p. 162). Searching for neighborhood watch (NW) Programs may facilitate engaging in informal social control or collective efficacy.

Bennett et al. (2006) conducted a systematic review of 36 NW program evaluations and revealed that 53% of the evaluations (19 studies) resulted in desirable changes in crime. Desirable change was defined as a greater reduction or a smaller increase in crime. Other evaluations showed uncertain (11 studies) or undesirable effects (6 studies). The researchers then conducted a meta-analysis of 18 program evaluations where they found desirable effects for three-quarters of the evaluations. The researchers concluded that NW programs brought small, desirable reductions in crime. According to crime solutions, a government-funded evaluation of U.S. crime prevention programs, NW is rated as effective for offender prevention but ineffective for victimization prevention, particularly in socially disorganized communities (Holloway et al. 2008; Office of Justice Programs 2018).

In this study, we investigate Internet searches as a new and emerging factor in crime prevention, including: (1) target hardening, (2) surveillance, (3) formal social control and (4) informal social control. To our knowledge, only two studies exist examining the relationships between Google searches and crime; we review these studies below.

Google searches

As previously noted, a number of studies have been conducted using Google search data to understand human behavior (Stephens-Davidowitz and Pinker 2017). Gross and Mann (2017) sought to understand factors that impact public attitudes toward police violence given the rise in U.S. homicide rates from 2014 to 2016. The researchers compared the patterns of Google search activity related to the *Black Lives Matter* movement using Google AdWords and the Major Cities Chiefs Police Association data on violent crimes reports. Gross and Mann (2017) found that in U.S. cities where violent crime increased, there were increases in Google searches related to police violence. Search rates were higher in cities with greater representations of minorities and youth,

and in areas with intensive policing strategies (Gross and Mann 2017). Search volume rates peaked in high profile events such as the police-involved shootings of Eric Garner and Freddie Gray.

Gamma et al. (2016) analyzed the relationship between annual methamphetamine-related crime statistics and Google Trends search data on "meth" in Switzerland, Germany, and Austria from 2004 to 2016. Gamma et al. (2016) found a sharp rise in methamphetamine related criminal offenses and police activity from 2010 to 2014. During this same time period, Google "meth" search activity sharply rose. In both studies, crime-related searches were correlated with actual levels of drug and violent crimes. Thus, further examination of Internet searches and crime patterns is needed.

The current study

The goals of this study are to answer three research questions:

1. Are higher rates for property crime associated with searches for crime prevention information?
2. Are increased levels of crime prevention searches associated with reductions in property crime?
3. If there is a reduction, what is the magnitude of that reduction?

To answer these questions, this study uses Google Correlate data paired with UCR property crime data to examine state-level variations in Google search patterns and variations in overall property crime, larceny-theft, burglary, and motor vehicle theft.

Methodology

Google Correlate data

Over three billion searches are conducted on Google each day in the U.S. (Statcounter 2018). We used Google Correlate (2017), a publicly available online data interface, to access crime prevention query data. Google Correlate incorporates an algorithm that allows the user to input either state-level or time series data from external sources, and then identifies Google queries that are correlated with external data (Stephens-Davidowitz and Pinker 2017). The algorithm is atheoretical and typically identifies many queries that are highly correlated with the external dataset but are often spurious. We adapted Google Correlate by introducing query terms derived from existing crime theories rather than relying on the algorithm to select terms based on the strength of correlations. The crime prevention queries were entered into Google Correlate interface to generate standardized measures expressed as z-scores.

Theoretical classification of Google search terms

Building on previous research, we examined two mechanisms and three techniques from the SCP classification system to identify crime prevention queries. The key mechanisms included increasing the offender's: (1) perceived effort and (2) perceived risks (Clarke 1992; Clarke and Homel 1997; Hough et al. 1980). Target hardening is an example of the first mechanism whereas formal and natural surveillance are examples of the second mechanism. We also applied concepts from the CCP literature to select Google searches related to formal and informal social control (Weisburd et al. 2014; Welsh and Farrington 2014). Thus, our crime prevention search categories included: (1) target hardening, (2) surveillance, (3) formal social control, and (4) informal social control. We selected these search terms because these crime prevention approaches are known to reduce criminal opportunities and crime (Cohen and Felson 1979; Felson and Boba 2010; Sampson et al. 1997; Shaw and McKay 1942). Table 1 provides a listing of query categories and terms.

Uniform crime report data

We used property crime data from the FBI's UCR. UCR (2014) data are structured into four categories: (1) overall property crime index, (2) burglary, (3) larceny-theft,

Table 1 Crime prevention Google queries

Target hardening	Surveillance	Formal social control	Informal social control
Deadbolt	Alarm system	How to file a police report	Neighborhood crime
Door locks	Car alarm system	Report crime	Neighborhood security
Gate keypad	Home alarm system		Neighborhood watch
Security door	Home security camera		Neighborhood watch sign
Window bars	Home security system		
	Motion detection camera		
	Motion detection lights		
	Street lights		

and (4) motor vehicle theft. The UCR defines burglary as "the unlawful entry of a structure to commit a felony or a theft"; larceny-theft is "the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another"; motor vehicle theft is "the theft or attempted theft of a motor vehicle"; and the overall property crime index is a composite measure of the foregoing property crime types. Property crime rates were calculated as state-level incidents of crimes per 100,000 population (United States Department of Justice 2017).

Merging Google query data with UCR property crime data

Merging Google data with traditional datasets such as government-provided UCR data is inherently challenging. The Google Correlate dataset is massive and contains queries combined from 2003 to the present. On the other hand, UCR data are collected on an annual basis but availability normally lags by 1 or 2 years. To combine the two datasets, we used Google Correlate data from January 2003 to the collection period, June 2017, as our base dataset. Next, we selected UCR data with the closest time approximation to the Google series, which was UCR data from 2003 to 2014. Since Google Correlate z-scores are aggregated measures of queries over the 14-year period, we also aggregated the UCR property crime data over the 12-year period that overlapped with the Google queries. Hence, our merged dataset is primarily multi-year averages of both crime prevention Google queries and UCR data at the state-level.

We calculated two measures of property crime. First, average rate of property crime was calculated as the aggregated average of state-level crime data from 2003 to 2014. Average rates were carried out for all four categories of property crime. Second, the reduction in property crime was calculated as the annual rate of reduction for each state as well as a summary measure of the total reduction in crime from 2003 to 2014.

Results and discussion

State level property crime trends

A cursory review of UCR data indicated that property crime in the U.S. consistently declined during the period of our investigation. The decline occurred in almost every state with North Dakota being the one exception, and it had a stable property crime rate.

Property crime rates and Google searches

In the first set of analyses, we assessed whether higher property crime rates (calculated as state-level incidents per 100,000 population) were associated with higher rates of Google search queries for crime prevention. In Table 2, Pearson correlations are reported between the four property crime indicators and Google crime prevention queries yielding 76 correlations. Of these correlations, 66 (86%) were found to be statistically significant at the 0.05 level or below. This finding supports the notion that higher levels of property crime are associated with increased levels of Google searches across a wide range of crime prevention approaches. Higher rates of motor-vehicle theft were strongly correlated with surveillance queries for "car alarm system" ($r = 0.800$, $N = 50$, $p < 0.01$); high burglary rates were strongly correlated with "home alarm system" ($r = 0.776$, $N = 50$, $p < 0.01$). The surveillance queries produced stronger correlations than target hardening queries. For example, queries for "alarm system", "car alarm system", "home alarm system", and "home security system" all yielded correlations greater than 0.500.

There were significant positive correlations between social control queries and property crime rates. Formal social control measures produced some of the highest correlations. Individuals in high crime states were more likely to seek information about filing a police report or reporting crime. Across the categories, "how to file a police report" held the strongest association with motor vehicle theft ($r = 0.829$, $N = 50$, $p < 0.01$). However, queries for informal social control produced weak to moderate correlations for all property crimes.

Google searches and reductions in property crime rates

In the preceding sections, we found that the level of property crime in a state was correlated with the level of Google searches for crime prevention. In this section, we investigated whether Google searches for crime prevention were correlated with *reductions* in property crime. The correlational analysis in Table 3 indicated that 57.8% of crime prevention queries were significantly correlated with crime reduction. In states with higher levels of target hardening queries such as "gate keypad", and "security door", those states had higher correlations with overall crime reduction. Also, surveillance queries for "alarm systems", "car alarm systems" "home alarm systems" and "street lights" were associated with reductions in several types of property crime.

Google queries for the social control categories were associated with property crime reduction. The strongest correlation ($r = -0.629$, $N = 50$, $p < 0.01$) was the formal social control query, "how to file a police report". This query was correlated with all types of property crime. This suggests that acquiring knowledge of how to interact with the police concerning incidents of crime was associated with crime reduction. Informal social control queries "neighborhood crime", "neighborhood security", and "neighborhood watch sign" yielded statistically significant correlations

Table 2 Correlations between property crime rates and Google queries for crime prevention terms

Search terms	Overall property crime rates	Burglary rates	Larceny-theft rates	Motor vehicle theft rates
Target hardening				
Deadbolt	0.471**	0.436**	0.391**	0.432**
Door locks	0.395**	0.427**	0.324*	0.267
Gate keypad	0.766**	0.782**	0.635**	0.573**
Security door	0.480**	0.419**	0.323*	0.725**
Window bars	0.253	0.321*	0.078	0.499**
Surveillance				
Alarm system	0.695**	0.794**	0.510**	0.580**
Car alarm system	0.568**	0.461**	0.420**	0.800**
Home alarm system	0.688**	0.776**	0.485**	0.661**
Home security camera	0.434**	0.569**	0.301*	0.290*
Home security system	0.616**	0.725**	0.454**	0.475**
Motion detection camera	0.346*	0.393**	0.244	0.321*
Motion detection lights	0.289*	0.244	0.241	0.305*
Street lights	0.196	0.007	0.126	0.606**
Formal social control				
How to file a police report	0.622**	0.514**	0.469**	0.829**
Report crime	0.428**	0.375**	0.277	0.679**
Informal social control				
Neighborhood crime	0.461**	0.344*	0.378**	0.585**
Neighborhood security	0.457**	0.299*	0.430**	0.475**
Neighborhood watch	0.493**	0.483**	0.357*	0.571**
Neighborhood watch sign	0.425**	0.377**	0.304*	0.572**

Source Google Correlate, FBI uniform crime reports

* $p < 0.05$, ** $p < 0.01$

with all categories of property crime. Increased searches related to organization of neighborhood programs appeared to be associated with property crime reduction.

However, we found a low correlation between "neighborhood watch" and reduction in property crime. Neighborhood watch is the generic term for many informal approaches to social control, yet this search term had weaker correlations with property crime rates than other variables. We found that an anomaly occurred during the data series that may have weakened the impact. During the year 2012, two events produced large spikes in queries for "neighborhood watch". The first event was the Trayvon Martin case in Florida that sparked interests in neighborhood watch programs and their negative consequences. The second event was the release of the movie *Neighborhood Watch* which also generated a large number of Google queries. It can be argued that these two incidences likely produced non-crime reduction related queries and consequentially the strength of the correlations may be reduced.

The magnitude of crime reduction associated with Google queries

Our correlational analysis revealed that states with higher levels of property crime tended to have higher levels of crime prevention searches. Furthermore, we found that states with higher levels of crime prevention searches tended to experience higher reductions in property crime. We now address the magnitude of the crime drop associated with queries. To conduct this analysis, we grouped states into high, mid, and low groups based on the relative frequencies of queries for the four crime prevention categories. We then calculated the average 12-year reduction in overall property crime for each group and then conducted a series of One-Way ANOVAs.

Table 4 presents the results of ANOVAs comparing mean crime reduction between high, mid, and low search groups. The greatest differences occurred between

Table 3 Correlations between the rate of property crime decline and Google queries for crime prevention terms

Search term	Overall property crime rates	Burglary rates	Larceny-theft rates	Motor vehicle theft rates
Target hardening				
Deadbolt	−0.141	−0.135	−0.098	−0.169
Door locks	−0.066	−0.053	−0.055	−0.066
Gate keypad	−0.412**	−0.493**	−0.343*	−0.299*
Security door	−0.539**	−0.385**	−0.385**	−0.712**
Window bars	−0.106	−0.085	0.076	−0.470**
Surveillance				
Alarm system	−0.305*	−0.389**	−0.128	−0.485**
Car alarm system	−0.549**	−0.457**	−0.380**	−0.707**
Home alarm system	−0.347*	−0.401**	−0.154	−0.562**
Home security camera	−0.024	−0.079	0.045	−0.126
Home security system	−0.137	−0.206	−0.009	−0.303*
Motion detection camera	−0.227	−0.327*	−0.122	−0.275
Motion detection lights	−0.246	−0.322*	−0.132	−0.323*
Street lights	−0.428**	−0.174	−0.318*	−0.628**
Formal social control				
How to file a police report	−0.530**	−0.461**	−0.385**	−0.629**
Report crime	−0.265	−0.248	−0.091	−0.528**
Informal social control				
Neighborhood crime	−0.396**	−0.317*	−0.320*	−0.417**
Neighborhood security	−0.505**	−0.394**	−0.436**	−0.477**
Neighborhood watch	−0.278	−0.217	−0.202	−0.348*
Neighborhood watch sign	−0.379**	−0.358*	−0.296*	−0.384**

Source Google Correlate, FBI uniform crime reports

* $p < 0.05$, ** $p < 0.01$

the high search groups and the mid and low groups. For the target hardening search groups, the mean reductions in crime were not significant ($N = 50$, $p = 0.073$) between high ($M = -1179.629$), mid ($M = -806.738$), and low searches ($M = -880.165$). The surveillance groups ANOVA indicated significant reductions ($N = 50$, $p = 0.018$) in crime between high ($M = -1230.629$), mid ($M = -845.863$), and low searches ($M = -792.341$). Formal social control also resulted in the greatest significant reductions ($N = 50$, $p = 0.000$) in crime for high ($M = -1313.600$), mid ($M = -912.756$), and low searches ($M = -646.412$). Informal social control also experienced significant reductions ($N = 50$, $p = 0.003$) in crime for high searches ($M = -1258.665$) compared to mid ($M = -917.363$) and low searches ($M = -697.012$).

In Table 5, we present data comparing all 50 states for high, mid, and low searches and overall crime reduction. Arizona had the highest total crime reduction while North Dakota resulted in the lowest total crime reduction.

As depicted in Fig. 1, results showed the high search group was associated with the greatest changes in property crime drop trends from 2003 to 2014. Figure 2 revealed that the high search group was associated with the greatest reduction in overall property crime rates.

Conclusions

Google queries are organic, self-generated behaviors that leave digital footprints that researchers can use to understand human behavior. In evaluating correlations, it is important to consider the pervasiveness of Google. People conduct billions of searches daily based on their needs and concerns. Google searches can lead to information related to news, images, books, videos, maps, shopping, and finance. The Google search engine is a broad-based adaptation that humans use to solve some of their fundamental problems. It introduces a new technological variable into the matrix of factors underlying understanding of crime and crime prevention. Our research suggests that Google queries are playing a role in crime prevention. This study demonstrates that crime prevention queries are associated with significant reductions in crime over time. Searches are likely influenced by characteristics of places, such as local crime rates and

Table 4 One-Way ANOVA for high, mid, and low searches and the reduction in overall property crime

Factor	N	Mean	95% confidence interval for mean			*df*	Mean square	F	Sig.
			Std. deviation	Lower bound	Upper bound				
Target hardening									
High searches	17	−1179.629	562.211	−1468.692	−890.567				
Mid searches	16	−806.738	437.053	−1039.627	−573.848				
Low searches	17	−880.165	442.722	−1107.791	−652.538				
Between groups						2	652,049.2	2.771	0.073
Within groups						47	235,288.9		
Total	50	−958.486	502.294	−1101.236	−815.736	49			
Surveillance									
High searches	17	−1230.629	538.500	−1507.500	−953.758				
Mid searches	16	−845.863	366.034	−1040.908	−650.817				
Low searches	17	−792.341	486.183	−1042.313	−542.369				
Between groups						2	965,634.6	4.351	0.018
Within groups						47	221,944.8		
Total	50	−958.486	502.294	−1101.236	−815.736	49			
Formal social control									
High searches	17	−1313.600	472.746	−1556.664	−1070.536				
mid searches	16	−912.756	426.262	−1139.895	−685.617				
Low searches	17	−646.412	373.201	−838.294	−454.529				
Between groups						2	1,916,448	10.56	0.000163
Within groups						47	181,484.7		
Total	50	−958.486	502.294	−1101.236	−815.736	49			
Informal social control									
High searches	17	−1258.665	475.418	−1503.102	−1014.227				
Mid searches	16	−917.363	480.094	−1173.187	−661.538				
Low searches	17	−697.012	400.61	−902.986	−491.037				
Between groups						2	1,360,575	6.632	0.003
Within groups						47	205,138.8		
Total	50	−958.486	502.294	−1101.236	−815.736	49			

other demographic, economic and political composition factors.

In speculating on the underlying explanations for the correlations between crime prevention queries and crime rates, it is important to discuss the Internet activity that often occurs behind searches. Many of the queries in our study involved target hardening and surveillance related products that can be purchased online. In fact, part of the influence of the queries may be that they activate consumer surveillance practiced by online retailers. For example, when searching for home alarm systems, people will receive a number of links for suggested sites. With additional views and clicks, potential consumers may be identified as entities interested in security related products and marketed not only for home alarm systems but for a wider range of crime prevention products. In states where crime prevention queries were the most intense, it seems reasonable that the power of the Internet marketplace is more readily brought to bear upon crime prevention commerce.

However, there are several limitations to the use of Google Correlate data. First, we cannot control for non-spuriousness or time order. Due to the cross-sectional nature of data and the fact that our analyses are bivariate, we have no way of knowing whether changes to crime patterns cause searches or whether searches lead to changes in crime patterns. Future research should control for population size, violent crime rates, and socioeconomic characteristics of each state as these factors likely influence this relationship. Second, it is important to recall that Google Correlate data is only available at the aggregate, state-level thus it is difficult to apply theories that are best intended for application at the micro-level, such as the street-level (Eck et al. 2017). Third, it is difficult to identify the motives of a searcher (Gamma et al. 2016; Gross and Mann 2017). For instance, it is unclear whether a person is searching

Table 5 High, mid, and low search and overall crime reduction by states

State	Target hardening		Surveillance		Formal social control		Informal social control		Average		Total crime reduction
	Rank	z-score	Rank	z-score	Rank	z-score	Rank	z-score	Rank	z-score	
Alabama	H	0.31	H	0.89	M	−0.22	M	0.36	H	0.34	−868.8
Alaska	M	−0.03	M	−0.34	H	0.62	H	0.51	M	0.19	−1001.6
Arizona	H	1.72	H	1.09	H	1.19	H	0.48	H	1.12	−2436.5
Arkansas	H	0.32	H	0.49	L	−0.57	M	−0.26	M	0	−294.4
California	H	0.5	H	0.41	H	1.84	H	0.99	H	0.94	−985.3
Colorado	M	0.21	M	0.08	H	0.9	M	0.36	H	0.39	−1421.5
Connecticut	M	−0.13	M	−0.21	L	−0.78	L	−0.68	L	−0.45	−746.1
Delaware	M	0.03	M	0.02	M	−0.03	L	−0.55	M	−0.13	−433.3
Florida	H	1.07	H	0.96	H	0.77	H	0.51	H	0.83	−1041.8
Georgia	H	0.27	H	0.74	H	0.67	H	0.72	H	0.6	−978.5
Hawaii	H	0.78	H	0.91	H	0.43	H	0.77	H	0.72	−2224.6
Idaho	L	−0.51	L	−0.76	M	−0.12	L	−0.57	L	−0.49	−1074.3
Illinois	M	−0.31	M	−0.17	H	0.2	H	0.55	M	0.07	−1212
Indiana	L	−0.38	M	0.29	M	0.07	H	1.15	H	0.28	−706.3
Iowa	L	−0.88	L	−0.81	L	−0.91	L	−0.94	L	−0.89	−882.2
Kansas	L	−0.82	L	−0.34	L	−0.58	L	−0.85	L	−0.65	−1275.2
Kentucky	M	−0.07	M	0.11	M	−0.08	M	−0.24	M	−0.07	−263.2
Louisiana	H	0.26	H	0.86	H	0.5	H	0.49	H	0.53	−851.7
Maine	L	−0.85	L	−0.96	L	−0.98	L	−1.09	L	−0.97	−463.8
Maryland	H	0.5	H	0.83	H	1.14	H	0.54	H	0.75	−1291.6
Massachusetts	L	−0.66	M	−0.3	L	−0.48	L	−0.4	L	−0.46	−705.7
Michigan	L	−0.39	M	−0.21	M	−0.08	M	0.06	M	−0.16	−1234.7
Minnesota	L	−0.67	L	−0.38	M	−0.11	H	0.49	M	−0.17	−815.8
Mississippi	M	0.06	M	0.19	L	−0.64	L	−0.48	M	−0.22	−786.1
Missouri	M	−0.29	M	0.14	M	−0.2	H	0.59	M	0.06	−1177.4
Montana	M	−0.21	L	−1.13	L	−0.53	L	−0.9	L	−0.69	−623.3
Nebraska	L	−0.69	L	−0.42	M	−0.27	L	−0.56	L	−0.49	−1228.4
Nevada	H	1.7	H	1.16	H	2.25	H	1.13	H	1.56	−1661.8
New Hampshire	L	−0.49	L	−0.39	L	−0.68	L	−0.57	L	−0.53	−90.2
New Jersey	M	0.08	M	0.08	L	−0.31	L	−0.53	M	−0.17	−815.5
New Mexico	H	1.66	H	0.6	H	0.77	M	0.22	H	0.81	−546.8
New York	H	0.43	L	−0.54	M	0.14	L	−0.55	M	−0.13	−530.8
North Carolina	M	0.22	H	0.6	H	0.18	M	0.11	M	0.28	−1397.8
North Dakota	M	−0.13	L	−1	L	−1.3	L	−1.06	L	−0.87	0.4
Ohio	M	−0.3	M	0.13	M	−0.18	M	−0.13	M	−0.12	−851
Oklahoma	H	0.67	H	0.95	H	0.24	H	0.97	H	0.71	−1321.6
Oregon	L	−1.2	L	−0.9	M	−0.23	M	−0.31	L	−0.66	−1886.6
Pennsylvania	M	−0.22	M	−0.04	L	−0.29	M	−0.14	M	−0.17	−498.5
Rhode Island	L	−0.4	L	−0.47	L	−0.82	M	−0.06	L	−0.44	−821.6
South Carolina	H	0.32	H	0.5	M	0.18	H	0.55	H	0.39	−1061.4
South Dakota	L	−0.72	L	−1.22	L	−1.57	L	−1	L	−1.13	−139.5
Tennessee	H	0.63	H	0.69	H	0.37	M	0.39	H	0.52	−1328.7
Texas	H	0.33	H	0.73	H	0.97	H	0.39	H	0.61	−1580.5
Utah	M	0.13	M	−0.12	M	0.14	M	0.34	M	0.12	−1376.6
Vermont	L	−0.78	L	−1.25	L	−1.37	L	−0.83	L	−1.06	−704.3
Virginia	L	−0.76	L	−0.43	M	−0.07	M	−0.02	L	−0.32	−791.2
Washington	H	0.52	H	0.77	H	1.93	H	0.84	H	1.02	−1048.9

Table 5 (continued)

State	Target hardening		Surveillance		Formal social control		Informal social control		Average		Total crime reduction
	Rank	z-score	Rank	z-score	Rank	z-score	Rank	z-score	Rank	z-score	
West Virginia	M	0.11	M	−0.06	M	−0.25	M	0	M	−0.05	−304.3
Wisconsin	L	−0.71	L	−0.72	L	−0.69	M	−0.03	L	−0.54	−792.1
Wyoming	L	−0.51	L	−1.22	L	−2.93	L	−1.18	L	−1.46	−1350.9

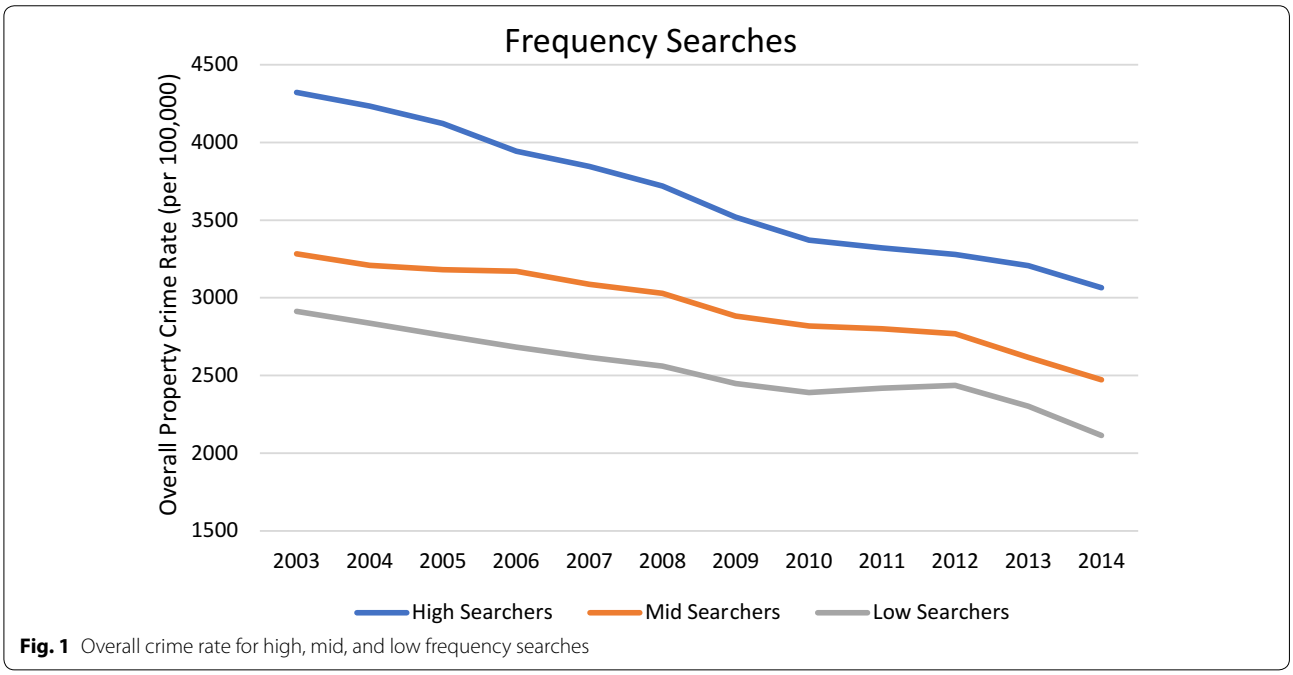

Fig. 1 Overall crime rate for high, mid, and low frequency searches

for "gate keypad" as a crime prevention tool, whether a potential offender is searching to identify its vulnerabilities, or something else entirely. Relatedly, Google searches about crime prevention may not always lead to actions. Thus, it would be valuable to have data that identified actions, such as aggregate-level data for actual target hardening and surveillance related purchases through online retailers. Fourth, it is challenging to find Google search terms that approximate theoretical constructs. The language of 'everyday life' used in many Google searches are quite different from the language used in crime theory. Consequently, close proxies of concepts may be lacking. For example, "how to file a police report" may not clearly be a preventative search. These limitations are important to examine in future research and theoretical development in the area of big data and crime prevention.

Google data, then, like many big data sources, are inherently messy and troublesome to incorporate in traditional crime science methods. Nevertheless, the widespread availability of computer and Internet technology makes Google and other search engines accessible to large segments of the population and is relatively easy to scale up and utilize to address almost any question or information needs that researchers may have.

Our research revealed empirical data patterns that are consistent with the perspectives and hypotheses of situational opportunity and community theories of crime. The findings demonstrate that new emerging technologies, such as Google, are utilized to acquire information about crime prevention and that the use of these technologies for crime prevention knowledge may be contributing significantly to crime reduction. Also, Google queries need not be the result of governmental programs that seek to reduce crime. Rather, in many ways Google searches are more of a Do-It-Yourself (DIY) approach to crime prevention.

Our research points to the need for additional theoretical work that incorporates emerging technologies as an adaptive strategy in crime prevention. The rapid

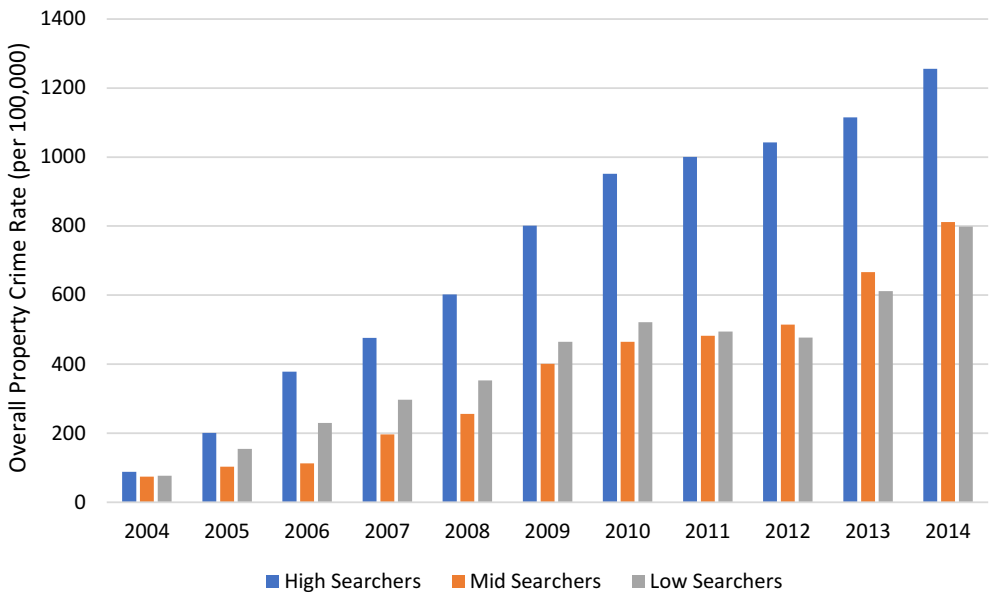

Fig. 2 Cumulative reduction in overall crime rate

expansion of information technology, big data, and associated approaches can be expected to become a critical part of crime theory. Sampson (2011) has begun to call attention to this need via his proposal of incorporating technology-mediated efficacy into research. Research has shown online activism can lead to improved offline activism when it comes to violent sexual crimes (Mendes 2015); however, more work is needed to assess how online activism applies to the reduction of traditional property crime.

Technology-mediated efficacy may improve all types of crime prevention due to increased knowledge acquisition. One way to improve community engagement with technology-mediated efficacy for crime prevention would be to increase Internet access across places. This suggestion is in line with Carr's (2003) recommendations for improving social control efforts to reduce crime. In this way, residents could be introduced to locally organized programs where trained professionals, local volunteers, and law enforcement could teach the community how to use new technology to prevent crime. Such efforts could also involve local police departments and local counties or councils on how information about crime prevention strategies can be found and accessed via Google. For example, law enforcement could release monthly newsletters with crime prevention tips online to increase community engagement and government transparency. To develop such programs, key stakeholders in the area of crime prevention, big data, and emerging technologies would be crucial for successful implementation.

In closing, we wish to point out that like all powerful technologies, Google queries have the potential for creating societal harm as well as societal good. While our research documented certain beneficial aspects of Google queries for property crime prevention, it is certainly obvious that the capacity of the Internet is allowing the creation of new forms of criminal behavior, such as cyber-crime (e.g., terrorism, bullying, fraud) as well as the expansion of underground criminal networks. Given the pace of technological development, it is likely that the utilization of novel forms of human-generated data, such as Google, will become an important source of information for crime science.

Abbreviations

DIY: Do-It-Yourself; CCTV: Closed Circuit Television Camera; FBI: Federal Bureau of Investigation; NW: Neighborhood Watch; UCR: Uniform Crime Report; U.S.: United States.

Authors' contributions

MSR conceptualized the study design applying crime concepts to Google Correlate data; contributed to the discussion of crime literature throughout the manuscript; contributed to the methods, study findings, discussion section, and editing of the manuscript. AKC collected, merged, and analyzed UCR data with Google Correlate data for this study; contributed to the methods section of the manuscript. KDB contributed to the discussion of Google Correlate and Internet-based research findings throughout the manuscript; contributed to the methods, study findings, discussion section, and editing of the manuscript. AGC conceptualized the study design; led data analyses for the manuscript; and contributed to the methods, study findings, and discussion of the manuscript. All authors read and approved the final manuscript.

Authors' information

The authors are affiliated with the Innovative Data Laboratory located at the Social Science Research Center (https://ssrc.msstate.edu/). The lab focuses on

the utilization of emerging and novel data sources to investigate a wide range of social science research issues.

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Competing interests
The authors declare that they have no competing interests.

Availability of data and materials
All data are publicly available online. Links to the data are provided below. Search terms used to create the Google Correlate dataset are provided in Table 1.

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United States Department of Justice, Federal Bureau of Investigation (2014). *UCR Data.* Retrieved from https://www.bjs.gov/ucrdata/Search/Crime/State/TrendsInOneVar.cfm.

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