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Suicide prevention-related Google searches and subsequent emergency department visits in California and Arizona, 2007–2015

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Abstract

Introduction: United States emergency departments (ED) visit rates for nonfatal self-harm increased by 42% from 2001 to 2016. Previous suicide mortality research has provided conflicting evidence on the use of suicide-related Internet searches as a surveillance tool for self-harm and suicidal ideation. However, few have used rigorous approaches to account for autocorrelation at the aggregate level, and none have focused on Internet searches related to suicide prevention.

Methods and results: Over a 9-year study period (2007–2015), suicidality-related search data were extracted using the Google Health Application Programming Interface (API) for Arizona and California – states, chosen for their differing age distributions and rigorous ED injury coding policies. We examined several combined suicide prevention-related search queries. Using autoregressive integration moving average (ARIMA) models and a Box-Jenkins approach, we assessed whether increased prevention-related Internet searches related to suicidality are predictive of lower subsequent ED visits related to suicidal ideation with or without self-harm injury. In both states, greater prevention-related queries were associated with lower ED visits approximately four to six weeks later.

Conclusions: Our results indicate that Internet-based search volumes related to suicide prevention may have the potential to monitor suicidality and online suicide prevention resources offer meaningful opportunities for mental health support.

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CRediT authorship contribution statement

Hilary L. Colbeth: Writing – original draft, Visualization, Validation, Methodology, Conceptualization. **Sidra Goldman-Mellor:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Ellen A. Eisen:** Writing – review & editing, Methodology. **Krista Neumann:** Writing – review & editing, Methodology. **Ralph Catalano:** Writing – review & editing, Methodology, Formal analysis. **Corinne A. Riddell:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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Keywords

Time-series analysis; Suicidal ideation; Emergency departments; Google search; ARIMA models

1. Introduction

Suicidal behavior is a major public health challenge in the United States. In 2019, nearly 5% of U.S. adults report having experienced serious suicidal thoughts in the past year (*Mental Health Information: Suicide*, 2022), and between 2001 and 2019, there was a 40% increase in the age-adjusted rate of emergency department (ED) visits for deliberate self-harm, a proxy measure for suicide attempts (*Nonfatal Injury Reports 2000–2019*, 2022). Patients presenting to EDs for suicidality are at high risk for repeat self-harm and subsequent suicide (Goldman-Mellor et al., 2019), underscoring the importance of tracking this indicator of population mental health. However, data on ED utilization are typically only released after lags of a year or more, hindering efforts to respond to trends in a timely manner.

The Internet is a popular resource for seeking help and information related to mental health and suicidality (Recupero et al., 2008). It is seen as more confidential and less stigmatizing than seeking care from a mental health professional (Burns et al., 2010). On one hand, the Internet could have detrimental effects by exacerbating risky cognitive beliefs around belongingness and burdensomeness (via suicide-related forums or chat rooms) or facilitating suicide planning in an anonymous setting (Chan et al., 2017). However, prominent theories of suicidal behavior suggest that the Internet could have salutary effects by addressing, via suicide prevention-oriented websites, high-risk individuals' distorted cognitive beliefs and facilitating access to life-saving information (Joiner, 2005; Klonsky & May 2015; O'Connor and Kirtley, 2018; Sueki and Ito, 2015). Recognizing the potential for the Internet to play a role in suicide prevention, in 2010, Google implemented automatic resource guides (e.g., links to the National Suicide Prevention Lifeline) that are returned in response to suicide-related searches (Zeiger, 2010).

Research investigating the association between Internet search query volumes and suicide outcomes at the population level have reported mixed results. Some studies found that an increase in suicide-related Internet search activity is associated with a rise in suicide death rates (Barros et al., 2019; Capron et al., 2021; Gunn and Lester, 2013; Hagihara et al., 2012; Lee, 2020), but others directly contradicted this conclusion (Kristoufek et al., 2016; Marchant et al., 2017; Sueki, 2011). Many studies, however, used broadly-defined search terms (e.g., "depression," "divorce," "unemployment") and focused on suicide fatalities as the outcome. Moreover, Tran et al. (2017), have noted that past studies often suffer from methodological shortcomings, such as few data points, Google search trend patterns that depend on the specific day the query is conducted, and time-series analyses that did not account for autocorrelation shared by searches and indicators of suicidal ideation or behavior.

The inconsistencies of the literature across locations and settings (Barros et al., 2019; Capron et al., 2021; Gunn and Lester, 2013; Hagihara et al., 2012; Kristoufek et al., 2016; Lee, 2020; Marchant et al., 2017; Sueki, 2011) suggest that the drivers of

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suicide rates may differ by place, time-period, and that the data may be prone to selection bias. For example, individuals who actively seek help online may be maximally responsive to Internet-provided prevention resources. These concerns, highlight the need for continued work using longitudinal state or national-level data, methods that control for time-dependent autocorrelation, and research that examines more precise Internet query-response relationships (Tran et al., 2017).

In this study, we contribute to the literature by adjusting for time-series temporal patterning and then investigate the hypothesis that prevention-related Google search queries will show an inverse correlation with subsequent ED visits for suicidal ideation in California and Arizona. To our knowledge, this study will be the first to examine the impact prevention-related Google search data, which may capture those open to receiving confidential mental health resources. Both states were chosen because they employed rigorous ED injury coding practices. Although several previous analyses of Internet searches and suicide used mortality as an outcome (Barros et al., 2019; Hagihara et al., 2012; Kristoufek et al., 2016; Lee, 2020; Sueki, 2011); we believe it is pertinent to focus on ED visits because non-fatal suicidal behavior is far more common than suicide death and tends to be concentrated among younger individuals (Borges et al., 2010), who may use the Internet at higher rates.

2. Material and methods

2.1. Search terms

We initially compiled 54 search terms that we identified as related to suicidality. Terms that were ambiguous with respect to suicide prevention (e.g., we did not include the phrase 'I don't want to live', which does not by itself convey an intent for suicide prevention) were discarded. We then searched for our phrases of interest using a Google Incognito browser to ensure that the results were consistent with those experiencing suicidal ideation or self-harm intent, and excluded search phrases that did not appear relevant. The final list included the following 6 suicide prevention-related searches: *prevent my suicide*, *suicide help*, *suicide hotline*, *suicide prevention*, *suicide prevention reddit*, and *suicide* support *group*.

2.2. Query collection

After processing search terms of interest, the Google Health Application Programming Interface (API) (Matsa et al., 2017) returns a scaled proportion of all searches within a specified geo-time period. To obtain the search data from the API, the researcher must first apply for an API key. Search terms, geographic region, and the time period of interest must be entered by the researcher, and the API will return a probability of the search terms for the specified geo-time period calculated based on a randomly generated sample of all searches that were uniquely generated daily and cached for 24 h (Matsa et al., 2017; *The Next Chapter for Flu Trends*, 2015). As such, the same query produces different results when performed on a different day. The returned results are based on a random sample of all Google searches and then scaled by 10 million for readability (*2020 Google Trends API Getting Started Guide*, unpublished document provided with the API key). The API output is interpreted as a relative search volume with an unknown denominator, since the total number of searches used to calculate the returned probability is unknown to the researchers.

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We conducted state-level queries at monthly intervals within Arizona (1/1/2007–12/31/2015) and two-week intervals within California (1/1/2009–12/31/2013). The study periods differed by state due to outcome data availability. Our two-week time-periods for California search queries capitalized on the state's larger population and were able to detect sub-monthly variation in our independent and dependent variables; however, Arizona's smaller population size precluded using this approach. For each state's geo-time-periods, we pulled 10 random query samples (meaning, one pull per 24-h, repeated over 10 24-h periods) from the API. As suggested by Tran et al., we then averaged across the 10 pulls to reduce random variability in the API's data generating process (Tran et al., 2017).

Python (version 3.8.5) and the search sampler package and function (version 1.0.1) (*Search Sampler*, 2018) were used to query the Google Health API.

2.3. Emergency department data

ED data for Arizona were obtained from the Healthcare Cost and Utilization Project Statewide Emergency Department Database (*Healthcare Cost and Utilization Project (HCUP): Overview of the State Emergency Department Databases (SEDD)*, 2021). Emergency department data for California were obtained from the California Office of Statewide Health Planning and Development. Both Arizona and California datasets contained encounter-level information on all ED visits in the state made by patients 10 years or older. In AZ, encounters included ED treat-and-release visits and the ED visit portion of encounters that resulted in an inpatient admission to the same hospital; in CA, encounters additionally included those that resulted in an inpatient admission to a different hospital (Wier et al., 2013). As with the Google search volume data, California ED data were combined into two-week intervals, while data for Arizona remained at monthly intervals.

2.4. Suicidality measures

We retained all visits with an International Classification of Diseases, Version 9, Clinical Modification diagnosis for suicidal ideation (V62.84), in any diagnostic position (*International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM)*, 2015). Suicidal ideation visits could have a comorbid diagnosis for deliberate self-harm, but this was not required. Deliberate self-harm visits were defined as those with an external cause-of-injury code of E950.0–958.9, in any diagnostic position. Arizona and California were chosen because these states have mandated 100% reporting of external cause-of-injury codes for many years, and reporting is considered virtually complete (Abellera et al., 2005).

2.5. Statistical analysis

Time series data frequently exhibit autocorrelation in the form of trends and cycles (e.g., seasonality), and have a tendency of high or low values to persist, although diminished, in subsequent observations (Helfenstein, 1996). We used Box-Jenkins methods (Box et al., 2015) (also known as "autoregressive, integration, moving average", or ARIMA models) to detect autocorrelative patterns in suicide-prevention related Google searches and suicide-related ED visits to estimate values expected from those patterns. These methods have been widely used in the sciences, including epidemiology (Bruckner et al., 2016; Catalano et

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al., 2021; Catalano and Serxner, 1987). ARIMA models express trends and strong cycles as products of integration (Box et al., 2015). These models use moving averages and autoregression to capture patterns in the data such as periods of elevated or depressed values, or patterns of oscillation. To determine which combination of ARIMA parameters best describe autocorrelation, we iteratively fit models following well-developed rules and “goodness of fit” testing (Box et al., 2015).

First, we used ARIMA methods (Box et al., 2015) to identify and model autocorrelation in suicide prevention-related Google searches originating from Arizona and California and in the incidence of suicide-related ED visits in those states. The fitted values of the models served as our expected values. We then regressed model residuals (i.e., observed minus expected values) for ED visits on model residuals for Google searches and estimated the Pearson correlation coefficient to quantify the strength of association between the two series after removing the patterns identified in the ARIMA models. We estimated correlation coefficients for the synchronous (i.e., both variables measured in the same month) as well as for 3 “lagged” configurations (i.e., Google searches precede ED visits by 1, 2 and 3 months). For both states, we inferred support for our hypothesis if at least 1 of the 3 lagged correlations fell below the 95% (2-tailed test) confidence interval, meaning, there was evidence consistent with our hypothesis that earlier suicide-related Google searches were associated with later ED visits.

We used Scientific Computing Associates’ time series processor for all statistical analyses (Liu, 2009). This study was approved by the Institutional Review Board at [anonymized].

3. Results

Table 1 shows the best fitting ARIMA models for prevention-related Google search time-series and for ED visits for suicidal ideation with or without self-harm, in both states.

Figs. 1 and 2 (panel A) display Google search volumes for Arizona and California, respectively, plotted as points over time with the fitted values from the Google search ARIMA models shown in the solid lines. Monthly Arizona suicide prevention-related terms Google search volumes ranged from 35 to 279 with a mean of 131 over 105 test months starting January 2007 and ending September 2015. California Google search volumes ranged from 126 to 439 with a mean of 214 over 130 two-week intervals starting January 2009 and ending December 2013. Figs. 1 and 2 (panel B) also display Arizona and California suicidal ideation-related hospitalizations plotted over time as points which closely surround the fitted values, shown as solid lines, from the ARIMA models. The average number of monthly ED visits for suicidal ideation in Arizona was 1,115 with a range of 579 to 1,633. In California, over 130 two-week periods, the average number of ED visits was 2,665 with a range from 1,843 to 3,846. The upward trend shown in Figs. 1 and 2 for ED visits required that their respective ARIMA equations include, as indicated in Table 1, differencing to render the series stationary in their means.

Correlation coefficients that measured the association between residuals of the ARIMA models for searches and the residuals of the ARIMA models for ED visits, by state, are

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described in Table 2. Consistent with our hypothesis, searches using suicide prevention terms are inversely related with subsequent ED visits for suicidal ideation, in both states. Meaning, increased Google search volumes were associated with reduced ED visits in the following weeks to months. For example, in Arizona, prevention-related searches are inversely associated with ED visits one month later ($r = -0.29$; $p < 0.01$). In California, prevention searches were inversely correlated with ED visits 3 two-week periods (i.e., 1.5 months) later ($r = -0.24$; $p < 0.01$).

We then pursued an additional analysis to test the robustness of our results and to provide estimates of associations perhaps more intuitively meaningful than correlation coefficients (Eggers et al., 2021). We estimated correlation coefficients for Google searches and ED visits 1, 2, and 3 time periods *later* (Table 2) (Eggers et al., 2021). As shown in Table 2, none of the placebo coefficients were statistically significant, aligning with our hypothesis that changes in Google searches predict changes in ED visits but not vice versa.

4. Discussion

We evaluated the utility of suicide prevention-related Google search data as a tool to monitor emergency department utilization for suicidal ideation (with or without self-harm). To our knowledge, this is the first study that (a) employed Box and Jenkins techniques that reduce autocorrelation and secular trends in time-series data and (b) explored Internet search terms' predictive ability for non-fatal suicidal behavior outcomes, an underdeveloped area of population-level suicide research. Overall, our results suggest that increased search volume for prevention-related suicidality terms is predictive of lower ED visit rates – an association that was consistent across two states.

In both states, the Google search volumes had some potential to signal mental health distress at the population level. For example, greater suicide prevention-related searches, such as *suicide hotline*, were related to lower ED visits in the following month in Arizona. These types of searches likely trigger Google's suicide prevention algorithm to display the National Suicide Prevention Lifeline immediately under the search bar, and a preventive effect of this display (and a call to the Lifeline) (Zeiger, 2010) could explain the time-delayed negative correlation.

Our findings are aligned with existing theoretical contributions around so-called "practical capability for suicide," (Klonsky & May 2015) which refers to the capacity of a specific factor to make suicide attempts easier. However, if the Internet is one such factor, it could also contribute to reducing suicidality by helping individuals find community and/or decreasing shame, thereby increasing hope and belongingness (Klonsky & May 2015). Growing evidence suggests that the Internet can be an influential avenue for public suicide education and mental health support via suicide prevention campaigns, addressing frequently asked questions, and online outreach and support platforms for people experiencing mental distress (Day et al., 2013; Lipson et al., 2019). Campaigns such as the National Suicide Prevention Lifeline (We Can All Prevent Suicide) and The Trevor Project (Get Help Now - The Trevor Project) are aimed, in part, at improving the recognition of suicide risk and increasing help-seeking (Mann et al., 2005). Our study results support the

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efforts of current and future online platforms that offer support for those undergoing mental health distress, as the use of such resources may contribute to the prevention of subsequent hospital visits for suicidal ideation. In addition, future research can continue this work by monitoring and forecasting changes in suicide prevention-related search trends to accelerate real-time understanding of population suicidality risk.

The contrast between our results and those from some previous research reporting positive associations between search volumes and suicide rates (Gunn and Lester, 2013; McCarthy, 2010; Yang et al., 2011) may be due to several factors including our specific use of prevention-related Google searches, the dependent time-series being ED visits for suicidal ideation rather than suicide mortality and, finally, including evolving time-series analyses methods that express trends and cycles as products of integration (Tran et al., 2017). Our results align with other studies using applied time-series analysis methods investigating links between Google searches and suicide attempts and suicide rates (Bruckner et al., 2014; Solano et al., 2016).

Our study has several limitations. The Google search data were limited to English-language terms and restricted to searches in two U.S. states. Our study cannot determine what proportion of searches were generated by individuals at risk of suicide versus their friends and families, medical providers, or other individuals. The autocomplete features of Google may influence the search behavior of users and may prompt them to perform other searches than originally intended. Individuals entering suicide-related prompts may also be using websites that promote anonymity or anonymize a user's true internet protocol address; such searches would not populate our queries in the Google Health API. In addition, the search terms used in this study are not comprehensive and may not comprise the extent of prevention-related Google searches that convey that help was wanted for suicidality and suicidal intent. Since the Google Health API does not provide information on user demographics, we were not able to incorporate any sex- or age-specific Google data into the analysis. Finally, further investigations of suicide help-seeking Google searches might consider their relation to suicidal ideation inpatient admissions reported in HCUP's State Inpatient Database (*Healthcare Cost and Utilization Project (HCUP): Overview of the State Inpatient Databases (SID)*, 2021). It is possible that increased Google searches for prevention may be followed by an increase in suicidality-related inpatient admissions, which would be only partially observable in the Arizona SEDD database used in the study. However, the study's California data included all inpatient-admitted ED visits for suicidal ideation, and we did not observe increased suicidality-related visits after increased Google searches in that state.

This study possessed several strengths. We applied ARIMA time-series analysis methods in addition to averaging ten time-series per search term, which is crucial to increasing the reliability of Google search data (Tran et al., 2017). We also analyzed search data with resolutions at monthly and two-week intervals, which may have detected changes in Google search volumes with more accuracy than searches with longer time frames, and concentrated on the specific impact of prevention-related Google search terms, a first in the literature regarding Internet searches and suicide. Lastly, we focused on ED visits for suicidality, an

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important and relatively frequent outcome often overlooked among studies examining the feasibility of using Google data for behavioral forecasting.

5. Conclusions

We found consistent associations between higher volumes of search terms related to suicide prevention and help-seeking behavior and lower ED visits for suicidality and posit that Internet searches may offer a potential avenue for public mental health monitoring.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sidra Goldman-Mellor reports financial support was provided by National Institutes of Health. Hilary L. Colbeth reports financial support was provided bys National Institute for Occupational Safety and Health. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Abbreviations:

API	Application Programming Interface
ARIMA	Autoregressive, integration, moving average
ED	Emergency department

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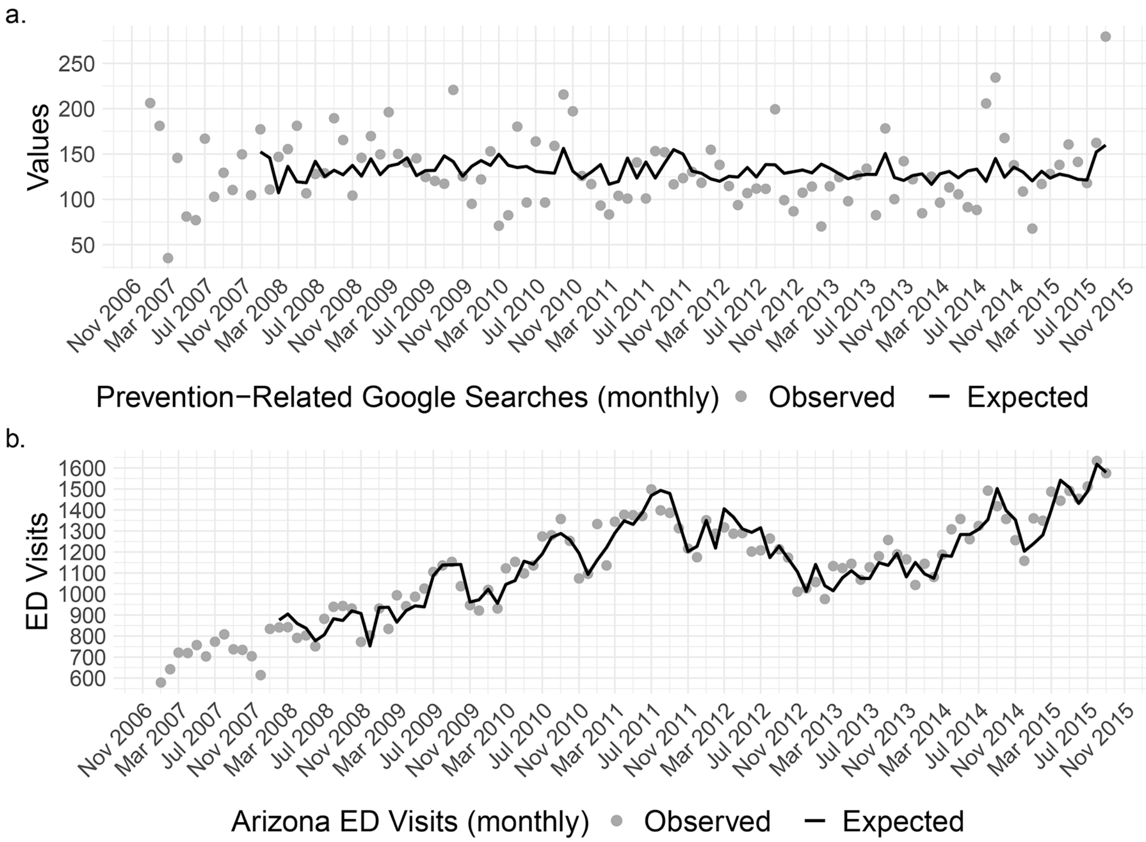

Fig. 1.

Scatter plot (observed) and best fitting line of detrended (expected) (a) Google searches for suicide prevention-related terms and (b) emergency department (ED) visits for suicidal ideation with or without self-harm across 105 months in Arizona, 2007–2015.

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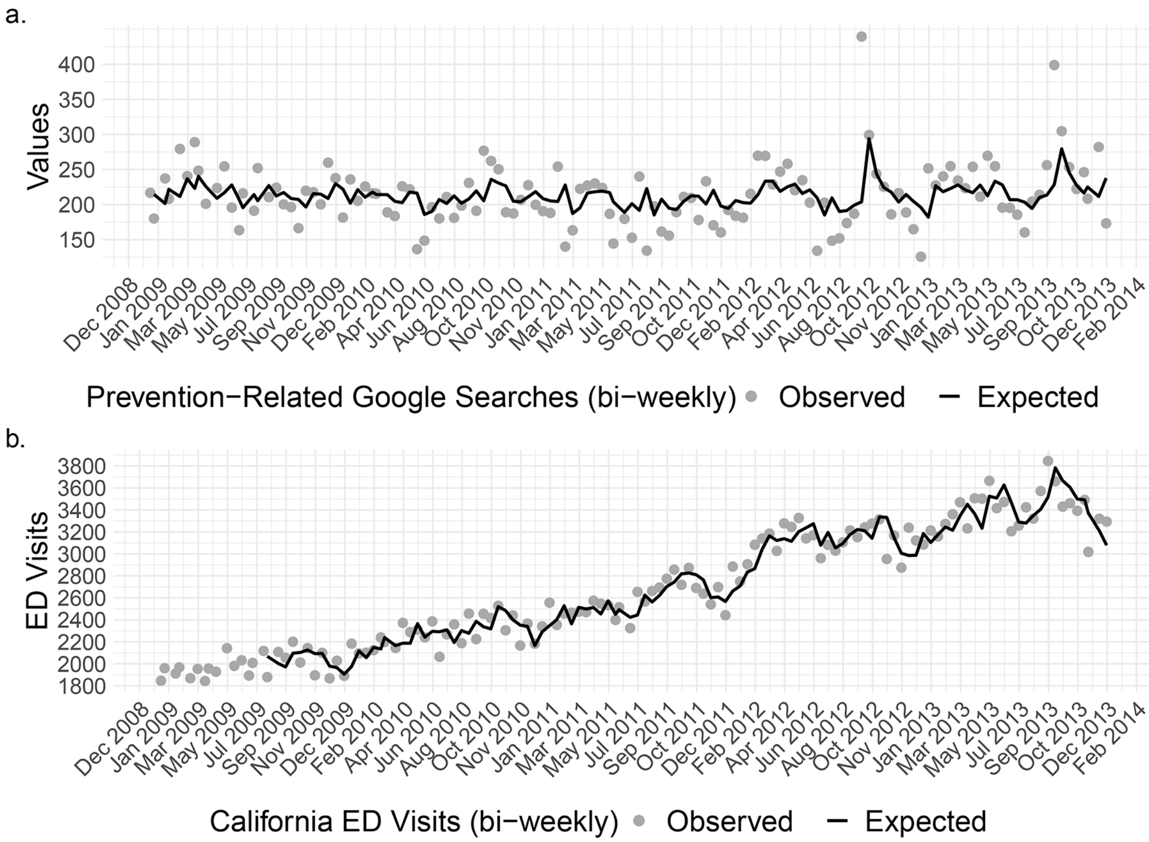

Fig. 2.

Scatter plot (observed) and best fitting line of detrended (expected) (a) Google searches for suicide prevention-related terms and (b) emergency department (ED) visits for suicidal ideation with or without self-harm across 130 two-week intervals in California, 2009–2013.

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Table 1

Box-Jenkins equations for suicide prevention-related Google searches and for emergency department (ED) visits for suicidal ideation with or without self-harm in Arizona (monthly, 1/2007–12/2015) and California (two-week intervals, 1/2009–12/2013). All estimated values are at least twice their standard errors.

State	Variable	Time interval	Box-Jenkins equation
Arizona	Google searches	months	$Y_t = 133.12 + 1/(1–0.26B^{12})a_t$
	ED visits	months	$(1\text{-}B)y_t=(1–0.31B)/(1–0.67B^{12})a_t$
California	Google searches	2 weeks	$Y_t = 213.37 + 1/(1–0.36B)a_t$
	ED visits	2 weeks	$(1\text{-}B)y_t = 1/(1 + 0.46B)(1–0.43B^{13})a_t$

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Table 2

Cross-correlation coefficients of detrended suicide prevention-related Google search time-series and the time-series for emergency department visits for suicidal ideation with or without self-harm in Arizona (monthly, 1/2007–12/2015) and California (biweekly, 1/2009–12/2013). [a]

	Google searches precede ED visits by			Both series in same time interval	Google searches follow ED visits (placebo) by		
	3 time intervals	2 time intervals	1 time interval		1 time interval	2 time intervals	3 time intervals
Arizona (month intervals)	0.02	− 0.01	− 0.29 [b]	−0.07	0.13	0.04	0.17
California (two-week intervals)	−0.24 [c]	−0.12	0.04	−0.04	0.17	0.1	0.07

[a] Each time-series is detrended through Autoregressive, integration, moving average (ARIMA) modeling and results are estimated through the cross-correlation of ARIMA model residual time-series for Google searches and ARIMA model residual time-series for emergency department (ED) visits, by state.

[b] $p < 0.01$; 2-tailed test; 92 degrees of freedom.

[c] $p < 0.01$; 2-tailed test; 115 degrees of freedom.