The Instagram Effect:
Is Social Media Influencing Visitation to Public Land?

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Public lands in the United States have recently experienced significant increases in visitation. Journalists and park managers suggest Instagram, a social media platform, as a reason for this increase. We explore this issue in Oregon State Parks by combining visitation data with park-specific geotagged photos and engagement indicators on Instagram. Using several model specifications, we show suggestive evidence that the introduction of Instagram and georeferenced content on the site are not likely to increase visitation everywhere, but only in a few places with high engagement within the app. We also find both contemporary and dynamic effects on visitation from geotagged posts to Instagram at these high engagement parks. (JEL Q26, Q50, Z30)

Across the nearly 640 million acres of public land in the United States (U.S.), managing agencies such as the National Park Service (NPS), Bureau of Land Management (BLM), and the U.S. Forest Service (USFS) rely on nearly half a billion visitors a year for revenue through user fees and justification for maintaining current government funding levels (NPS 2020; BLM 2020; USFS 2020). In the 2000s, there were concerns about a measurable decrease in visitation to U.S. national parks (Poudyal et al. 2013; Stevens et al. 2014). Some studies suggested the decrease was partly attributable to short-term effects of travel reductions due to the 9/11 World Trade Center terrorist attacks (McIntosh et al. 2011; Stevens et al. 2014; Bergstrom et al. 2020). Others explored national macroeconomic indicators showing that recessional impacts are negatively associated with demand to visit national parks (Poudyal et al. 2013) and that entrance fees were not likely to be a factor in decreased visits (Factor 2007; Stevens et al. 2014; Bergstrom et al. 2020). More recently, visitation trends shifted back to pre-1990 trends, and these parks began to see consecutive years of record-breaking visitation (Bergstrom et al. 2020).

Increased visitation to public lands produces a dynamic tension for state and federal land managers responsible for both providing recreation opportunities and preserving wild places (e.g., Jakus et al. 2010; Dundas et al. 2018; Mansfield et al. 2008).[1] Journalists have attributed the growing crowds on public lands to the introduction of social media photo-sharing apps, in particular Instagram (Figure 1). Park managers attribute social media to an increase in 'selfie traps,' or locations of considerable natural beauty that attract large crowds of people using the popular self-portrait technique to post content on social media platforms.[2] This paper empirically investigates if the rise of social media, specifically Instagram, has played a role in the recent increase in visits to public land in the U.S. state of Oregon.

We combine monthly visitor counts to 44 Oregon State Parks with newly compiled data on park-specific geotagged posts and their engagement (i.e., likes and comments) within Instagram. Our goal is to as assess potential correlations between Instagram and its features and the

[1] At the state level, increases in visitation are quickly outpacing budget allocations to maintain recreational facilities and prevent environmental disturbances (Smith et al. 2019). Furthermore, many agencies are working with a significant backlog of deferred maintenance, including the NPS ($11.6 billion; NPS 2018) and the Oregon Parks and Recreation Department (OPRD) ($59 million; Mukumoto 2019). The concern of negative impacts from overuse, stagnating budgets and staffing levels coupled with aging infrastructure are major concerns facing such agencies in the coming decade.

[2] See CapRadio's Yosemiteland podcast episode 1 "Selfie Trap" for more background information: http://www.capradio.org/news/yosemiteland/2018/07/11/yosemiteland/yosemiteland/

observed increase in visitation to Oregon State Parks over the last decade. We find that on average across all parks in our sample, Instagram is not likely a contributing factor to increased visitation. Yet, when we subset parks into groups based on engagement levels within the app, we do find that a select few parks with high engagement are likely to see significant increases in visits attributable to Instagram (24%). We then use counts of geotagged posts per park and define influential posts based on engagement within the app. Our results suggest that in high engagement parks, geotagged posts may increase current visits by 3.5% and the cumulative effect of all influential posts (past and present) increases visitation by 3.4% per month. This suggests there is potential for both a contemporaneous and dynamic effect of geotagged images in Instagram on visitation, but again only for a select few parks with iconic or scenic landscapes that generate posts with high engagement within the app. Lastly, we demonstrate that geotagged posts are likely the Instagram feature of interest for visitation, as a model using the park with the highest engagement in our dataset (Smith Rock State Park) suggest no effect related to user-generated organizational posts via hashtags.[3]

Previous research suggests recreational visits to public land are likely to respond to a set of common factors like gas prices, population growth, economic variables like median income, unemployment rate, or consumer confidence indices (Oh et al. 2011; Poudyal et al. 2013; Stevens et al. 2014; Bergstrom et al. 2020) and weather (Dundas and von Haefen 2020). Visits may also shift in response to changes in designations (e.g., national monument becomes a national park; Weiler and Seidl 2004; Weiler 2006; Fredman 2007). The rise of social media presents another potential factor that may influence recreational visits (Miller et al. 2019; Ghermandi and Sinclair 2019; Wood et al. 2020) but linking within-app behavior from a social media platfrom empirically to visitation has not yet been attempted. Prior work has focused on using content from social media to aid in estimating visitation levels and understanding visitor use patterns (Wood, 2013; Sessions et al. 2016; Levin et al. 2017; Tenkanen et al. 2017; Fisher et al. 2018; Walden-Schreiner et al. 2018a, 2018b; Wilkens 2021) or assessing differences in data quality and usage among platforms (van Zanten et al. 2016; Manikonda et al. 2016; Levin et al.

[3] A hashtag is a user-generated organization tactic where individuals place a pound sign in front of an unspaced phrase. The tag is then searchable and allows the platforms algorithm to push the content to other users outside their network whom might be interested in the content. YouTube is a video sharing platform which also utilizes hashtags to expand viewership, as does the most recent fastest growing social media platform TikTok.

2017; Norman et al. 2017; Tenkanen et al. 2017; Heikinheimo et al 2018; Ghermandi and Sinclair 2019; Toivonen et al. 2019).

This research is first to our knowledge to empirically link social media content as a potential driver of visitation levels on public land. We introduce an empirical framework for incorporating social media data into models of recreation visitation. We estimate the impact of the sustained use of Instagram, along with using within-app behavior (posts and engagement), to test for impacts on observed recreational visits. Importantly, our results suggest Instagram is not likely to impact visits to all public land, just those places with iconic landscapes and other features users of the app find favorable. We also provide evidence that geotagged images and influential geotagged posts are a potential feature of Instagram that could be credibly driving visitation in high engagement parks. This work contributes to our understanding of how online behavior may translate to recreational visits for specific parks. Our results provide evidence to help public land managers understand and adapt to the emerging social media paradigm and improve stewardship of highly used natural resources.

This paper proceeds as follows. Section 2 discusses previous research using social media data in recreation applications and describes the advantages and disadvantages of using data from various platforms. Section 3 describes our data and the process for collecting and quantifying data from Instagram. Section 4 describes our estimation strategy and outlines our empirical models. Section 5 discusses our results and the final section concludes with policy implications and avenues for future research.

1. Social Media and Outdoor Recreation

Social media data provide researchers an opportunity to use new public information to represent human activity in a variety of environments. To explore the connection between social media and recreation, prior work has focused on developing visitation estimation methods and tracking visitor-use impacts. The number of geotagged photos posted at a park has been shown to reliably correlate with the number of visitors to a park (Wood, 2013; Sessions et al. 2016; Levin et al. 2017; Tenkanen et al. 2017; Fisher et al. 2018; Walden-Schreiner et al. 2018a, 2018b; Wilkens 2021). These findings have important practical applications for reducing the cost of data gathering across managing agencies as well as having the potential of understanding recreation at previously underreached areas due to limited data collection (Wood, 2013; Fisher et al. 2018;

Hausmann et al 2018; Walden-Schreiner et al. 2018a, 2018b). Data from social media have also helped researchers examine willingness to pay for ecosystem services (Keeler et al. 2015; Ghermandi 2018; Sinclair et al. 2018) and explore spatial and temporal distribution of visitor-use patterns using location preferences (van Zanten et al. 2016; Heikinheimo et al. 2017, 2018; Levin et al. 2017; Tenkanen et al. 2017; are Walden-Schreiner et al. 2018a, 2018b; Barros et al 2020). Captured imagery within uploaded content has been used to map changes and impacts to natural systems and land use (Antoniou et al. 2016; Silva et al. 2018; Toivonen et al. 2019)

Although useful, social media data does have some limitations. Such data does not fully substitute for an on-site collection of visits (Wood et al. 2020). Social media users are also likely not fully representative of all public land users (Wilkins et al. 2021. The accuracy of social media activity has been associated with the park popularity and should be used with caution (Tenkanen et al. 2017). Performance and accuracy of the data varies across social media platforms and may be linked to how platforms function and are utilized differently by their user base (van Zanten et al. 2016; Manikonda et al. 2016; Levin et al. 2017; Norman et al. 2017; Tenkanen et al. 2017). Flickr and Twitter tend to be the most frequently used data sources in research partly due to the accessibility of information through their respective Application Program Interfaces (APIs) (Heikinheimo et al 2018; Ghermandi and Sinclair 2019; Toivonen et al. 2019). Instagram has been shown to outperform Flickr and Twitter as a proxy for visitation (Tenkanen et al. 2017), but changes in data access to Instagram's APIs have made continuing research difficult (Heikinheimo et al 2018; Ghermandi and Sinclair 2019; Toivonen et al. 2019). A recent meta-analysis noted the concentration of social media measuring visitation is often aggregated across many years with very few using social media as a visitation proxy at smaller temporal scales (Wilkins et al. 2021). Furthermore, only one paper was noted to have used engagement behavior (i.e., the number of likes a photo receives) from the users within the app to explore correlation with visitation (Hausmann 2017; Wilkins et al. 2021).

Many of the top social media platforms have intrinsically different mechanisms for engagement and meet differing needs of its users. Toivonen et al. (2019) provide an in-depth breakdown of various social media sites and the general habits of the users. Facebook has the largest number of monthly users and provides a more closed social network where accounts are often private and community is built on mutual acceptance of friend requests to access one another's content. Twitter relies on content delivered as tweets, or 280 characters conveying thoughts or ideas. If the account is public, users can follow other users without sending a friend request. Twitter was the first site that popularized the hashtag (# symbol). Flickr and Instagram are media-sharing platforms utilizing rich visual content, often containing images of people's activities and on-site observations (Toivonen et al. 2019). Flickr is not as popular when compared to Instagram but it has been widely used in studying human-nature interactions (Toivonen et al. 2019; Wilkins et al. 2021).

Instagram was designed for mobile devices and rapidly grew after its release in October 2010. It is currently in the top five most popular social media sites when ranked by active monthly users. It has a similar networking process as Twitter. It registered one million active users in the first two months, rising to fifty million once it was acquired by Facebook and opened to Android OS in April 2012. There are currently over 1 billion monthly active users. The app contains features that organize users' shared photos under hashtags, geo-referenced locations (geotags) and *Explore* feeds, along with the options to generate storylines and use various photo filters. Public users share content with others outside their network by tagging via hashtag or geotag. Each method places the photo under a searchable URL page containing all other public account users' content with the same tag.[4] Instagram data provides an opportunity to count the number of photos uploaded in a given month under hashtags and geotags, along with engagement indicators (i.e., likes and comments), to compare it to actual visitation counts to these locations. The hypothesis is the number of photos uploaded in a month under a geotag or hashtags captures individuals that have either recently visited, are sharing memories of the location, or are linking some experience to the location via the tag chosen. Viewers of Instagram posts are provided information from the content shared in both the photo and the caption. The number of likes and comments each post receives captures an estimate of viewers who enjoyed the content and provides a measure of a post's impact on other users of the platform.

We focus on Instagram due to its large user base (1 billion active monthly users) and its reputation of having the ability for posts to "go viral" and become influential (i.e., high engagement with user base) within the app.[5] Content can be influential on Instagram because it

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[4] Profiles posting under a hashtag are organized under the public URL (*www.instagram.com/explore/tags/<hashtag>*). Geotag URLs are organized under (*www.instagram.com/explore/location/<LocationID>*).

[5] "Going viral" refers to when an image, video, advertisement, etc., is circulated rapidly on the internet. There is no predetermined amount quantifying whether or not an image has gone viral only that it is widely shared and viewed.

is more freely shared and instantaneously exposed to others outside their own social network through the app's more open organizational structure and mobile application. Instagram uses the embedded GPS coordinates within a photo and provides a suggested geolocations designated within the app.[6] Instagram geotags provide the georeferenced locations, often tied directly to an address of a beautiful view, a hard-to-find trailhead, or other natural features. Geotags can be searched by name under the search tab *Places.* They can also be created by a user and can be openly used by others. Since geotags are creatable, some "points of interest" locations have multiple geotags. Geotags and the precise locational information they provide to users is a key reason many in the news media are placing blame on Instagram for the influx of visitation rather than other social media platforms.

Other tagging processes include hashtags. Hashtags in Instagram have a unique ability to be followed by an individual user whereas geotags do not. For example, when someone follows #yosemite, photos of Yosemite Park will appear on the user's personal photo feed when opening the app. Instagram's *Explore* page builds content based on tracked behavior on the site, pushing highly influential content the algorithm deems potentially engaging and interesting to the individual user. The *Explore page* and content search via hashtags or geotags does not display content in chronological order and can vary across users even if they are searching the location at the same time. Though a given individual user's *Explore* and photo feed is unobservable, many of the photos featured have a high level of engagement in the form of likes and comments.

The use of precise location, such as geotagging, can inform numerous potential visitors about relatively unknown wilderness areas. Parks throughout the United States have been experiencing congestion in certain areas and are placing blame on social media sites (e.g., Figure 1). In 2018, Jackson Hole Travel & Tourism Board began a campaign directed at Instagram "Influencers" to stop geotagging photographs with exact locations (Holson 2018).[7] Similar campaigns have emerged endorsing tagging responsibly by swapping location-specific geotags with generic or more ambiguous locations (Wastradowski 2019; Merlan 2019).[8] While some groups are

The authors will use the word influential instead of viral. However, it should be noted given how the authors quantify influential post at a location, all viral posts are captured within influential indicators.

[6] Since the acquisition of Instagram by Facebook in 2012 the accuracy of geotagging of photos was discontinued, and geolocation of posts was enabled trough "Facebook places", points-of-interests which represent the centroid of a known location such as a shop or a town.

[7] Influencers are individuals with many followers, typically in the thousands, that endorse products, places and lifestyles through the content they share.

[8] Currently, the Leave No Trace Organization is considering an 8th principle regarding responsible geotagging.

attempting to deter visitors because of overcrowding, other tourism boards see opportunities to increase visitation by using Influencers. In 2014, Travel Oregon launched its "Seven Wonders of Oregon" campaign with both a promotional video and the use of Instagram influencers (McOmie 2014).

2. Data

To investigate the link between visitation to public land and components of Instagram, we start by collecting data on visits to units within Oregon's state park system. We obtain monthly visitor counts and details on available amenities for all properties managed by the Oregon Parks and Recreation Department (OPRD) from January 2002 to August 2019. The visitor counts are measured by car counters placed at entrances to a park and recorded by OPRD staff each month.[9] OPRD manages 254 properties and over 100,000 acres of public land in Oregon as of 2022. Each location has a varying number of amenities, including campsites, restrooms, beach access, fishing, viewpoints, surfing, swimming, kayaking, boat ramps, hiking trails, and playgrounds. Within these properties, 50 units hold the designation of state park, the most common classification in the OPRD system. The remaining units are designated as recreation areas and sites, scenic corridors and viewpoints, natural areas, or heritage sites. The focus of our analysis is on state parks as these units on average have more amenities, such as developed campgrounds, and more reliable visitor counts due to higher staffing levels as compared to other unit types. It is also advantageous to concentrate our analysis on sites with a similar classification to provide a common pool of substitutable park locations (Weiler et al. 2004; Weiler 2006; McIntosh et al. 2011; Poudyal et al. 2013; Stevens et al. 2014; Bergstrom et al. 2020). Many recreation visitation models aggregate total visits annually or group parks together to identify overall impacts of explanatory variables (Weiler et al. 2004; Weiler 2006; Poudyal et al. 2013; Stevens et al. 2014; Bergstrom et al. 2020). We do not aggregate visitation data as our goal is to estimate the impacts of Instagram activity on park-specific visitation at relatively frequent intervals of time (i.e., monthly) following a similar approach as McIntosh et al. (2011).

Although there are 50 state parks, three (3) sites are removed from our dataset at the outset. Two parks (Bates and Cottonwood Canyon) were new additions to the OPRD system during our

[9] Car counters are standard traffic monitoring technology counting individual vehicles. Vehicles are recorded as they pass over a magnetic or weight sensor embedded in the road.

study timeframe (Jan. 2002 to Aug. 2019) and only existed as state parks after the launch of Instagram. Shore Acres State Park is removed due to large anomalies in the recorded monthly visitation counts relative to all other parks.[10] This narrows our dataset initially to 47 state park locations in Oregon.

Recreation visitation models typically start with the assumptions that visits are a function of travel cost, population, seasons, and other economic factors. As is common in this type of analysis, we do not observe individual travel costs decisions and use regional gasoline prices to capture temporal changes in travel costs (Oh et al. 2011; Poudyal et al. 2013; Bergstrom et al. 2020). Higher gas prices are likely to impact individuals' budget constraints, which may result in less visitors to park locations. Our recreation population is traveling throughout the Pacific Northwest, therefore regional inflation-adjusted conventional gasoline prices from the U.S West Coast (PADD5) are used here.[11] OPRD visitor surveys find a majority of visitors to Oregon State Parks live in Oregon (66%) and 65% of visitors travel more than 31 miles to reach a park (Bergersen, 2019). Following both economic theory and other research, population is used to control for the growth in the potential population of recreators (Poudyal et al. 2013; Bergstrom et al. 2020). Estimates of population for Oregon are collected from the Portland State University Population Research Center, dedicated to providing intermediate Oregon population estimates during the years between the national census conducted by the U.S. Census Bureau. We interpolate assuming linearity to match these estimates to the monthly time step of our empirical model.

Economics factors included in visitation models vary across the literature. Controls such as median income, personal savings, unemployment rate, business cycle index & consumer confidence index have been used previously (Oh et al. 2011; Poudyal et al. 2013; Stevens et al. 2014; Bergstrom et al. 2020). Poudyal et al. (2013) modeled each of these controls separately and found consumer confidence indicators provide an overall best fit for understanding and predicting National Park visitation levels. Our state-level focus here would likely benefit from state economic indicators rather than national trends and it is important to have a temporal match

[10] Shore Acres hosts several seasonal events not related to outdoor recreation (e.g., holiday lights show) that cause large variation in month-to-month visitation relative to all other parks as shown in Appendix Figure A.1 panel A. There are also two state parks directly adjacent to Shore Acres (Sunset Bay and Cape Arago; Figure A.1, panel B) which remain in the dataset and capture recreational visits to this area of the Oregon Coast. Therefore, Shore Acres is removed from the analysis.
[11] Gas prices are obtained from the U.S. Energy Information Administration https://www.eia.gov/.

with the economic indicators collected (Poudyal et al. 2013). Oregon's unemployment rate is among one of the economic factors which are actively measured monthly and considered a real time indicator of recessions (Saxton, 2008).[12] Our hypothesis follows Poudyal et al. (2013) where a higher unemployment rate will likely lead to reduced visitation to state parks. To control for local economic conditions and consumer confidence, we use a monthly value from Zillow's Housing Value Index for all homes in the state.

Recreation visits to parks are also likely influenced by weather. We obtain park-specific daily observations of temperature and precipitation in 4 km grid cells from Oregon State's PRISM Climate Group (PRISM 2020). Since our visitation data is reported monthly and our weather observations are daily, we follow Dundas and von Haefen (2020) and create a monthly distribution of daily maximum temperature outcomes using a binning approach. Each bin contains a count of the number of days within a month into 10 temperature bins with intervals set at a 10-degree °F scale ranging from less than 30°F to greater than 90°F (e.g., >30°F, 30-39.9°F, 40-49.9°F, etc.). This binning approach allows us to identify a non-linear effect of temperature - how an additional hot or cold day per month affects visitation. Rainfall is controlled for by using the monthly average precipitation in inches.[13]

2.1 Instagram Data

We collected data on all images on Instagram geotagged to 44 Oregon State Park locations (Figure 2) from the launch of Instagram in October 2010 until August 2019.[14] Two parks from the initial 47 were dropped at this stage (L.L. "Stub" Stewart and Alfred A. Loeb) due to Instagram server-side retrieval errors that prevented collection of geotagged images. A third, Prineville Reservoir State Park, did not have a park-specific geotag. Of the 44 parks for the analysis, twenty (20) are located on the Oregon coast, eleven (11) are within the Willamette

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[12] Indicators such as median income and personal saving are estimated quarterly for the state and are therefore not used in this analysis.

[13] A similar binning approach was attempted for precipitation. However, model results suggested the simpler monthly average was a better predictor for the impact of precipitation on monthly visitation.

[14] The 44 parks included are Beverly Beach, Bob Straub, Brian Booth, Bullards, Cape Arago, Cape Blanco, Cape Lookout, Carl G. Washburne Memorial, Cascadia, Catherine Creek, Collier Memorial, Cove Palisades, Ecola, Elijah Bristow, Fort Stevens, Guy W. Talbot, Harris Beach, Hat Rock, Hilgard Junction, Humbug Mountain, Illinois River Forks, Jessie M. Honeyman Memorial, Lake Owyhee, LaPine, Mayer, Milo McIver, Molalla River, Nehalm Bay, Port Oford Heads, Oswald West, Rooster Rock, Silver Falls, South Beach, Smith Rock, Starvation Creek, Sunset Bay, Tumalo, Umpqua, Valley of the Rogue, Viento, Wallowa Lake, Willamette Mission, William M. Tugman, and White River Falls.

Valley or Columbia River Gorge and thirteen (13) are parks within or east of the Cascade Range. The geotagged images and metadata are collected from public Instagram pages using a combination of a public domain Python code modified from Richard Arcega's "Instagram Scraper" & Instaloader.[15] The applications gathers information on the tag of interest (hashtag or geotag) and then crawls the URL where Instagram stores all public posts under the tag of interest visible to all Instagram users.[16] A JavaScript Object Notation (JSON) is produced with information on each post indexed by the date the photo was posted, the number of likes and comments each photo received and the caption. It does not collect demographic information on the user nor the Instagram bio.[17] The collected information allows us to calculate the number of geotagged uploads at each park every month and identify posts with high engagement by observing the number of likes and comments received by each post. We quantify these latter posts using the 90^{th} and 95^{th} percentiles of the amount of likes a post receives relative to the entire set of geotagged photos collected for the Oregon Park system.

Due to the nature of Instagram's algorithms and content delivery, photos with higher engagement are likely to be "sticky". Posts are considered sticky because as they accumulate more likes, they will also accumulate more views and be pushed to more users through engagement features within Instagram. These features include Instagram's *Top Post* of each individual location as well as being featured on Instagram's *Explore* page. Posts from a particular location that are featured by Instagram increases the likelihood users will discover the location. Each location has its own individual *Top Post* feature which means the most liked photos at a location can stick around for an undetermined amount of time. A high volume of likes also likely indicates some aesthetic or attractive quality that may influence recreators searching for information about visiting a site. We use these influential posts to generate a variable that can measure how posts with a high level of engagement within Instagram may correspond to overall visitation trends. We are interested in disentangling the contemporaneous effect of monthly geotagged uploads and the possible lingering influence that high engagement geotagged photos may have on specific parks. We examine this relationship by measuring the

[15] https://github.com/rarcega/instagram-scraper/tarball/1.8.1 ; https://github.com/timkiely/scrape-instagram-by-location
[16] Recent changes made to Instagram's API policy requires a user to be logged in to their account to view geotag post information. Until 2020, this information was viewable and accessible without logging in.
[17] An Instagram bio is a 150-character description under your username on your Instagram profile page. A bio is a chance to tell other a little about the account.

cumulative number of influential posts in all previous months for each park. This cumulative effect captures how much visitation will change in response to a permanent increase in influential posts for a given location. This variable addition will allow us to test for both a contemporaneous and dynamic effect of geotagged Instagram posts on visitation.

Our final dataset is a panel comprising 44 parks across 212 months. The panel is slightly unbalanced as there are a few parks that are closed in winter months (i.e., no visits) and a couple of instances where monthly visitation data is missing at a park due to random malfunctions of car counters collecting the information. Table 1 panels A and B provide aggregate summary statistics for our sample. Average monthly visitation to these state park units was approximately 32,000 over the sample frame. Post-Instagram visitation was slightly higher (~33,400/month) than pre-Instagram visitation (~29,900/month). Summary statistics for visitation, amenities, and Instagram geotagged posts by park unit is provided in Tables A.1 and A.2 in the online Appendix.

3. Estimation Strategy

Given that empirical estimation of the relationship between features of Instagram and visitation to public land is a relatively new endeavor, our empirical strategy is to start with a very simple model and then proceed to add complexity and address endogeneity concerns in subsequent steps. Our panel data structure allows for a fixed effects (FE) specification where we can control unobservable park-specific characteristics (Wooldridge, 2010). The first modeling specification examines the impact of Instagram's launch on visitation using a binary indicator to denote the pre and post periods (IG_{Launch_t}):

$$Ln\left(Visits_{pt}\right) = \beta_0 + \beta_1 IG_{Launch_t} + \beta_2 T_{pt} + \beta_3 Prec_{pt} + \beta_3 Ln(Gas_t) + \beta_4 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}\,, \tag{1}$$

where $Visits_{pt}$ is monthly (t) visits to park p, T_{pt} is a non-linear function of daily maximum temperatures per month that allows the marginal effect of weather to vary across park locations, $Prec_{pt}$ is the average monthly precipitation (in), and Gas_t is the average monthly inflation-adjusted conventional gasoline prices from the U.S West Coast. The vector X_t contains monthly economic controls for population growth, unemployment rate and the natural log of average housing prices, while $\rho_t, \tau_{y(t)}$, and γ_p represent month, year (y) and park fixed effects, respectively. The estimate of β_1 would reveal an average impact of the launch of Instagram on visitation to Oregon State Parks.

To further explore the potential for a visitation impact, we then consider that there may be significant variation among parks in how visitors and others engage with Instagram. Previous research has found social media activity is associated with park popularity (Tenkanen et al. 2017). To visualize this potential variation, we plot the Instagram engagement (number of likes) for every geotagged image associated with each of the 44 parks in our dataset. Engagement indicators are not illustrative of visitation but rather represent activity on the Instagram platform by those viewing the content of a posted photo. Figure 3 panel A displays this information, with parks ordered from least to highest level of engagement moving from left to right along the x-axis. The 30 parks on the left of the figure do have some limited engagement on Instagram, but the scale needed to capture the engagement for the parks on the right makes it appear to be near zero. Using the information from this graph, we partition Oregon's state parks into two groups, high and low engagement, with the hypothesis that there may be systematic differences in the effect of Instagram on visitation between these park types. Our preferred grouping uses the top 4 parks (Smith Rock, Oswald West, Ecola, and Silver Falls), displayed with black dots, as the high engagement group and the remaining 40 parks, displayed with gray dots, as the low engagement group. For examples of geotagged posts to Instagram from high engagement and low engagement parks, please see Figures A.2 and A.3 in the online appendix. We check the robustness of our high and low engagement park definitions through iterations that 1) expand the high engagement parks to the top 14; 2) drop the "middle 10" parks to compare the top 4 to the bottom 30, and 3) drop the top 4 and define the "middle 10" as high engagement.[18]

Comparison of summary statistics for this grouping of parks by engagement is shown in Table 1 panels C, D, and E. Importantly, the number of available amenities at parks in these groups is the same (11.8 on average), with low engagement parks having slightly more activity-based amenities (e.g., hiking, biking, kayaking) and high engagement parks having more scenery-based amenities (e.g., viewpoints). This suggests that high engagement parks may

[18] The "middle 10" parks are those in gray where the dots begin to appear above the baseline in Figure 3 panel A. These parks include Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverley Beach, and Sunset Bay. See Figure A.3 in the online appendix for visualizations of these alternative engagement groupings.

contain more "gramable"[19] park features. We also see differences between the groups in terms of Instagram geotagged uploads, with high engagement parks averaging 388 posts and 50 influential (90th percentile) posts per month compared to 31 and 2 per month in low engagement parks.

The next consideration is the timing of the impact of Instagram on park visitation. Our simple specification is eq. (1) assumes that Instagram may have an instantaneous impact on visitation. However, it is likely that simply the debut of a smartphone app is not an event that would systematically change visitation patterns. To help determine when Instagram would be likely to start influencing behavior, we plot the total geotagged uploads and influential posts (90th percentile) for all parks over time. In Figure 3 panel B, the first vertical line is October 2010 (Instagram's launch) and the second vertical line is April 2012. It is at this second line where we begin to see an increase in app usage associated with Oregon State Parks. This date (April 2012) also coincides with Instagram reaching fifty million active users worldwide, being acquired by Facebook, and releasing the app to Android phone operating systems (instead of just Apple iPhone iOS). In other words, April 2012 is likely to better represent the timing when Instagram may start having an influence on recreation behavior than the debut of the platform in October 2010.

Combining our park engagement grouping with new timing information about Instagram's potential impacts, we can estimate a difference-in-differences (DiD) specification of our model. While the experimental ideal would expose some parks to Instagram and not others to identify the impact on visitation, our high and low engagement grouping strategy has the potential to identify the impact of Instagram on parks with high engagement relative to those with low engagement. As noted above, parks in these two groups are similar in the observable number of amenities provided to visitors. Another common assumption needed for consistent estimation of DiD parameters is the parallel trends assumption. This requires that, absent the use of Instagram, the difference in visitation attributable to unobservables between park groups would have remained constant. We assess the validity of this assumption in Figure 4, which plots residual monthly visitation for high and low engagement parks before and after April 2012. The residuals arise from a regression of the natural log of monthly visits on all economic and weather controls

[19] Urban Dictionary: Social Media platform-specific adjective relating to Instagram. Something (mostly pictures) is good/fancy/interesting enough to post on Instagram.

and seasonal and region-by-year fixed effects that are then aggregated by group (high and low engagement) and month. The resulting figure suggest parallel trends are a reasonable assumption and that there may be systematic difference between high and low engagement parks post-April 2012.

We estimate the DiD specification as follows:

$$Ln(Visits_{pt}) = \beta_0 + \beta_1(High_p \ * IG_{Use_t}) + \beta_2 IG_{Use_t} + \ \beta_3 T_{pt} + \beta_4 Prec_{pt} + \beta_5 Ln(Gas_t) + \beta_6 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt} \ , \qquad (2)$$

where the interaction term of Instagram's sustained use ($IG_{Use_t} = 1$ post-April 2012) and an indicator for a high engagement park ($High_p$) estimates the effect of Instagram on visitation trends at these specific locations. All other variables are the same as defined for eq. (1).

Next, we specify additional models that use information about the content provided by Instagram, rather than just the existence of the platform itself. First, we use the park-specific Instagram data on the sum of geotagged uploads for each park per month ($Geotags_{pt}$). Our hypothesis is that these geolocated posts contain information to prospective recreators and could be the mechanism by which Instagram may drive changes in recreational visits to Oregon State Parks. We include IG_{Launch_t} to differentiate the months where a given location received zero uploads to Instagram from the time period which had no geotag uploads because Instagram did not yet exist. We specify this model as follows:

$$Ln(Visits_{pt}) = \beta_0 + \beta_1 IG_{Launch_t} + \beta_2 Geotags_{pt} + \beta_3 T_{pt} + \beta_4 Prec_{pt} + \beta_5 Ln(Gas_t) + \beta_6 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt} \ , \qquad (3)$$

Our next model uses geotagged posts in a manner analogous to our DiD specification (because a non-zero count of geotags implicitly includes $IG_{Launch_t} = 1$) by differentiating uploads by high and low engagement parks:

$$Ln(Visits_{pt}) = \beta_0 + \beta_1 IG_{Launch_t} + \beta_2(Geotags_{pt} * High_p) + \beta_3(Geotags_{pt} * Low_p) + \beta_4 T_{pt} + \beta_5 Prec_{pt} + \beta_6 Ln(Gas_t) + \beta_7 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt} \ , \quad (4)$$

where Low_p is an indicator variable defining low engagement parks. The next iteration of this model adds the cumulative count of influential posts at each park. This is done to disentangle the contemporaneous effect of monthly geotag uploads and the possible dynamic influence of highly influential posts ($\sum InfPost_t$) that can remain visible on Instagram from many months:

$$Ln(Visits_{pt}) = \beta_0 + \beta_1 IG_{Launch_t} + \beta_2(Geotags_{pt} * High_p) + \beta_3(Geotags_{pt} * Low_p) + \beta_4(\sum InfPost_{pt} * High_p) + \beta_5(\sum InfPost_{pt} * Low_p) + \beta_6 T_{pt} + \beta_7 Prec_{pt} + \beta_8 Ln(Gas_t) + \beta_9 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}\,. \tag{5}$$

Lastly, we use data from the park with the highest Instagram engagement (Smith Rock State Park (SRSP)) to explore a more nuanced understanding of features of Instagram and the relationship with visitation. We collected additional information on SRSP from Instagram in the form of hashtags to examine the difference between these two information features in Instagram. As noted earlier, geotags provide specific geo-referenced locations while hashtags provide the user with the name of the location along with other descriptive information (but not necessarily geo-location information). We want to be able to provide insight into the explanatory power of each social indicator (hashtag or geotag). We specify the single-park model as follows:

$$Ln(Visits_t) = \beta_0 + \beta_1 Tags_t + \beta_2 T_t + \beta_3 Prec_t + \beta_4 Ln(Gas_t) + \rho_{s(t)} + \tau_{y(t)} + \varepsilon_t, \tag{6}$$

where $Tags_t$ represents a monthly count of photos uploaded under either hashtags or geotags and $\rho_{s(t)}$ is a seasonal fixed effect. All models are estimated with robust standard errors.

4. Results

We begin by exploring the timing of Instagram's impact. Table 2 col. 1 and col. 2 show coefficient estimates based on the launch of Instagram (October 2010) and the observable use of Instagram (April 2012), respectively. Both models find no significant Instagram effect. In these models, other coefficients behave as expected. For example, higher gas prices are likely to reduce visitation and the temperature/recreation response function follows an inverted U shape, suggesting both high and low temperatures may decrease visitation (similar results to Dundas and von Haefen (2020)). See Table A.3 for full model results.

Our hypothesis is a simple debut of a smartphone app is not an event that would systematically change visitation patterns, nor would the impact be uniformly experienced across parks. Instead, the park engagement grouping determined by Figure 3 panel A provides a path to investigate how the use of Instagram and engagement level impact visitation in a DiD framework. Table 2 col. 3 and col. 4 displays results for a random and fixed effect specification of the DiD model. The random effect specification allows for the examination of the time invariant variables. The high engagement park indicator is time invariant which cannot be estimated using fixed effects. Both specifications find high engagement parks are on average experiencing significantly more visitation than low engagement parks due to Instagram. A Hausman test determined a fixed effects model (col. 4) is preferred. This model suggests high engagement parks have experienced a 24.1% increase in visitation relative to low engagement parks since Instagram gained in influence in April 2012.[20]

Next, we incorporate counts of geotagged posts into the model, using the variable IG_{Launch_t} to differentiate the months where Instagram did not exist from the months where Instagram did exist but did not have any geotag activity at a location. The effect of the sum of a geotagged uploads for each park per month for all 44 individual parks captures a positive association with visitation (Table 3 col. 1). The model suggests a marginally significant effect per geotagged image of 0.02 percent, which translates to a 1.3 percent contemporaneous effect in monthly visitation to the 44 parks within the model.[21] Our findings here support literature in other disciplines using geotagged photos to estimate and understand current visitation levels (Wood et al. 2013; Sessions et al. 2016; Walden-Schreiner, et al. 2018; Wilkins et al. 2021).

However, our findings in our previous specification suggest activity may differ by engagement level (Table 2 col. 3-4). Our next step separates geotags by high and low engagement parks (Table 3 col. 2). By separating the parks on engagement, we find the effect of geotags is only significant in high engagement parks and is the exact same magnitude as the model where we did not control for engagement level. A 0.02% increase per geotag translates to a total increase in visits to high engagement parks of 7.8%. This finding supports our hypothesis that Instagram activity is not likely impacting visitation to all parks but visits to parks which generate significant engagement within the app itself.

Furthermore, we examine the cumulative effect of influential geotagged posts for high and low engagement parks (Table 3 col. 3-4). Cumulative effects are interpreted as a permanent

[20] Percentage effect includes adjustment to coefficients to interpret a dummy variable in a semi-log equation (e.g., Halvoresn and Palmquist 1980).

[21] Average geotagged uploads post-Instagram to all parks is 63 post per month.

increase in the overall sum of influential geotag photos per month and its effect on park visitation. Cumulative effects allow influential photos of the past to influence current visitation. We examine the effect of photos in the top 90th and 95th percentiles separately based on the number of likes the photo received within high and low engagement parks. Again, we find that the only significant coefficients were associated with posts from high engagement parks. The sum of general geotag uploads to high engagement parks remains significant at the 10% level and suggest general upload activity increases contemporaneous visits by 3.4% in both influential post specifications. This is a little less than half of the contemporaneous effect captured in the previous model excluding the cumulative effect (Table 3 col. 2). The cumulative effect of influential posts from high engagement parks in both the 90th and 95th percentile is, on average, increasing visitation by 3.5% per month from all current and past influential photos.[22] Full results for these models are found in the online Appendix Table A.4. The significance of the cumulative effect suggests the overall impact of continual exposure has impacted visitation to certain parks over the last decade. The result also highlights how parks are not created equal and do not all have "gramable" qualities. Though low and high engagement parks have the same available amenities on average, high engagement parks differ in having at least one more scenery-based amenity while having less available activity amenities than the low engagement parks.

Lastly, we tested the differences between geotags versus hashtags in Smith Rock State Park (SRSP). The hashtag for SRSP (#smithrock) was collected providing an opportunity to investigate another potential feature of Instagram that may influence visitation. SRSP is the park with the most engagement, most influential photos, and a highly photogenic location with a variety of recreational opportunities (i.e., hiking, camping, rock climbing). In our models, geotags significantly correlated with overall visitation whereas hashtags did not (Appendix Table A.5). The divergence of these results matches our hypothesis on the provision of information being a potential mechanism driving increased visitation from social media posts. Geotagged photos provide specific information to potential visitor (e.g., location of a trailhead or beautiful vista) whereas hashtags represent many things for Instagram users, including sharing a memory or indicating a desire to go to a location by using a hashtag to categorize their photo. In other

[22] See Table 1 Panel C for average geotagged uploads and influential posts used to calculate the average effect when combined with coefficient estimates from Table 3 cols. 3 and 4.

words, hashtags encompass abstract organizational patterns when compared to the specific information provision provided by georeferenced location tags.

4.1 Robustness Checks

To test the robustness of our main findings, we alter the definition of high and low engagement parks. First, we moved the high engagement classification to the next visible break in Figure 3 panel A to include ten (10) more parks (Appendix Figure A.4 panel A). We then repeated all models. This definition found a 16% increase in visitation to high engagement parks. This result is less than our preferred model (24.1%) and estimated with slightly less precision (Appendix Table A.6). All geotags models, including those that include cumulative influential posts, yield similar results (Table A.7). The question then becomes is the addition of those 10 parks simply attenuating the impact of the top 4 or does it suggest the Instagram effect may impact more parks? To investigate, we specify models where the "middle 10" are dropped from the analysis (Appendix Figure A.4 panel B) so the models compare the original top four to the bottom thirty low engagement parks. These results suggest a 27.6% increase (table A.8) and a similar result for geotags (Table A.9). Lastly, if we drop the top four and treat the "middle 10" as high engagement (Figure A.4 panel B), we find no significant effect in the DiD specification (Table A.10) or the geotag models (Table A.11). The combination of these results suggests that it is likely that the effect of Instagram on visitation is limited to a few parks with very high engagement within the app and supports our primary modeling specifications.

5. Discussion

This paper attempts to quantify the role Instagram has played in the observable increase in visitation to state parks in Oregon in the last decade. While our initial models suggest no overall effect, we do find that the introduction of Instagram correlates with a 24% increase in visitation to certain Oregon State Parks which have high engagement activity within Instagram. We then present a variety of empirical specifications that find suggestive evidence of a connection between geotagging posts on Instagram and overall visitation. First, the effect of total monthly geotagged uploads suggests a 1.3% correlation to visitation for all parks in the model. When we isolate the effect of geotags by engagement level within the app, only parks experiencing high engagement on Instagram see a significant effect (7.8% increase in visitation). When controlling for the cumulative effects of influential photos on high engagement parks, general upload activity increases visits by 3.4% while the cumulative effect of either classification of influential photos suggests a 3.5% increase in visitation from all current and past influential posts. These findings support the claim influential photos from Instagram have impacted recreational visits but the impact is isolated to certain parks with high engagement within the app. This is likely due to inherent qualities of the high engagement parks which attract Instagram users for their "gramable" iconic viewpoints and landscapes. The Instagram effect of geotagging may not be a uniform impact but instead reflective of picturesque qualities inherent to certain parks.

Our findings that social media is impacting visitation to public land with high within-app engagement could be attributable to several potential mechanisms. One could be a reduction in search and information costs (e.g., Stigler 1961). Smartphone technologies have enabled discovery of new recreation locations and social media has provided a platform for individuals to share their experiences, discoveries and the location information among followers and friends. Instagram provides potentially valuable information in terms of discovery of new places or specific geo-referenced locational information on how to find beautiful viewpoints or natural features. However, if information costs were the sole mechanism, we would expect to see impacts at all locations, rather than just a small subset. Another potential mechanism is the bandwagon effect (or herd behavior), whereas an individual's demand for a commodity is increased due to the fact that others are also consuming the same good (Leibenstein 1950). This effect has been demonstrated in other contexts in economics (e.g., Biddle 1991), tourism destination preferences (e.g., Liu et al. 2019; Pan et al. 2021; Boto-García et al. 2022) and political science (e.g., Barnfield 2020). In this case, social media users would see others at these picturesque landscapes and choose to go there in order to not miss out on the experience and/or to obtain a similar photo of their own at a newly popular location. Although this research cannot determine the mechanism, it remains a viable area for future research.

This paper provides some validity to anecdotal claims that Instagram is a factor in the recent increase in visitation to public lands. However, the act of uploading geotags photos is not solely responsible for the rapid increase in visitation as some campaigns have claimed. Geotagging provides accessible park-specific information to potential recreators but it alone does not account for the increase. Instead, visitation increases are more correlated to engagement indicators within the app at specific locations. Our findings also suggest there are some unidentified ways in which

Instagram (or other social media) may influence visits to high engagement locations. Our interaction term of high engagement parks and the use of Instagram suggested a 24.1% increase in overall visitation to those parks. However, geotagged posts, at best, only accounted for 7.8% of this increase. Other social media sites and access to highly specific information at low-cost to potential recreators could account for some of the unaccounted visitation increases (e.g., Youtube, TikTok, AllTrails, Gaia, Twitter). Other potential changes could be the growing outdoor recreation economy (U.S. BEA 2020) and popularity of alternative lifestyles like van life (#vanlife) which often involves nomadic travel and recreational living in public land spaces (Monroe 2017). If these trends continue, a potential indicator for visitation increases to certain public land areas could be linked to the engagement these areas receive online. Public land areas have increasing accessible information provided by social media platforms and other outdoor websites. The site-specific information makes the outdoors more accessible to a greater number of individuals to find appreciation for our public lands but at the same time has potential negative impacts such as overuse and misuse of our public land resources. Instagram users have been blamed for ignoring signs in protected sensitive habitats and not practicing Leave No Trace (LNT) principles in order to get an "gramable" image (Canon 2019). In Deschutes County, Oregon, home of SRSP, there are already efforts such as *Tag Responsibly*, *Keep Bend Beautiful* focused on getting outdoor recreators to not reveal location-specific information on social media by using a broad, generic geotags when posting to Instagram (Wastradowski, 2019). Public shaming campaigns have developed to place pressure on ending the use of geotagging. Yet, it has also helped NPS find legal recourse against those who share evidence of their responsibility of resource degradation online (Schaffer 2015; Merlan 2019). Our findings suggest the growing concern should focus on influential engagement behavior encouraged by social media rather than the act of sharing the location alone.

One potential use of our results is informing park managers about how monitoring social media engagement could help them prepare for visitation surges. Influential photos and the amount of engagement a location gets online may be indicative of current and future visitation trends to the area. In pristine wilderness areas within sensitive habitats, this could be extremely important when monitoring online presence and potential increases in recreational use. Identifying abnormally high engagement online, i.e., "going viral", could help park managers prepare by focusing on mitigation strategies if overuse is a concern or target the engagement with backcountry information such as LNT to combat concerns of misuse. Land managers may also find justification for investing in the agency's social media presence as a low-cost informational pathway to directly connect with recreational users to educate and potentially mitigate negative future outcomes from overuse. This information could provide best recreational practices, site-specific location updates on resource closures, safe practices for viewing wildlife or trail information.

Another implication is a direct message for social media companies which provide user generated content a pathway to become influential or an influencer (Instagram, YouTube, TikTok, Twitter, etc.).[23] More available transparency to public agencies who manage the areas for which the geotag locations are being broadcasted to billions of users could be a potential public service for these publicly managed spaces. Allowing access to overall location engagement indicators could help identify changes to uploaded content and influential posts to inform potential management decisions. De-identified engagement indicators can be provided to agencies at various aggregated levels. In this paper, engagement indicators were obtained through a computationally intensive Python script that took many weeks to collect and is increasingly becoming more difficult given Instagram changes to its API permissions. This information could be made more readily available for park managers and researchers. Other helpful notifications to management agencies could be when verified public user accounts post under a given publicly managed geotag location. Verified public user accounts, as well as influencers, have a large audience increasing the probability an uploaded photo will become influential. Providing this type of transparency to public agencies entrusted to protect our public lands would be a service by social media companies who primarily make their profits off the data that their users provide for free in the form of user targeted advertising.

This research is an opening attempt at understanding the complex linkages between social media and recreation. Future survey research is needed to solidify the link between the timing of learning about a new recreation experience and then actually taking a trip. Linking individual trip choices rather than aggregate visitation with social media indicators would also open the door to a deeper understanding of this new outdoor recreation paradigm.

[23] An influencer is someone in a niche or industry with sway over a target audience.

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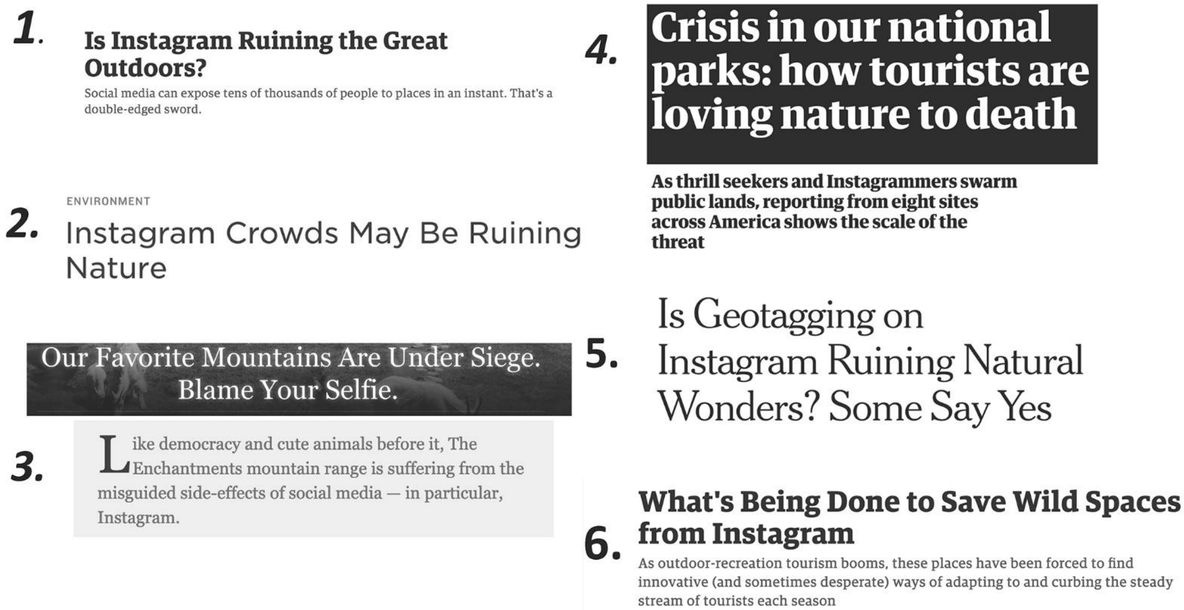

1. **Is Instagram Ruining the Great Outdoors?**
Social media can expose tens of thousands of people to places in an instant. That's a double-edged sword.

2. ENVIRONMENT
Instagram Crowds May Be Ruining Nature

3. Our Favorite Mountains Are Under Siege. Blame Your Selfie.
Like democracy and cute animals before it, The Enchantments mountain range is suffering from the misguided side-effects of social media — in particular, Instagram.

4. **Crisis in our national parks: how tourists are loving nature to death**
As thrill seekers and Instagrammers swarm public lands, reporting from eight sites across America shows the scale of the threat

5. Is Geotagging on Instagram Ruining Natural Wonders? Some Say Yes

6. **What's Being Done to Save Wild Spaces from Instagram**
As outdoor-recreation tourism booms, these places have been forced to find innovative (and sometimes desperate) ways of adapting to and curbing the steady stream of tourists each season

Figure 1: Social Media and Public Land

Note: This figure displays a variety of national and regional headlines about social media and growing visitation to public lands. 1. *Outdoor Magazine* Christopher Solomon Mar. 29, 2017; 2. *National Public Radio (NPR)* Lulu Garcia-Navarro Nov. 12, 2017; 3. *Oregon Public Broadcasting (OPB)* Ted Alverez Sep. 4 , 2018; 4. *The Guardian* Charlotte Simmonds, Annette McGivney, Patrick Reilly, Brian Maffly, Todd Wilkinson, Gabrielle Canon, Michael Wright and Monte Whaley, Nov. 20, 2018; 5. *New York Times* Laura M. Holson Nov. 29, 2018; 6. *Outdoor Magazine* Matt Wastradowski Apr. 5, 2019.

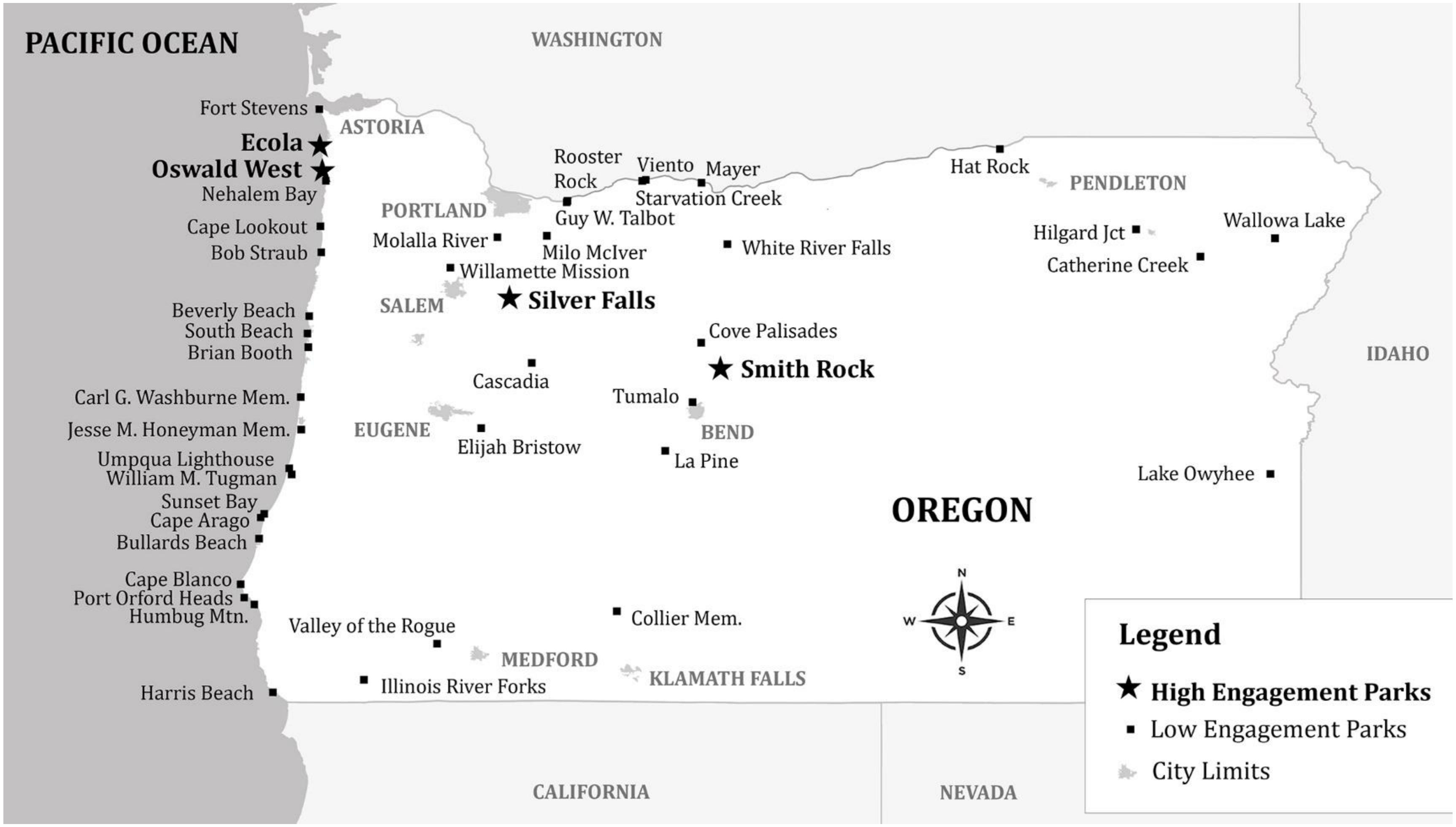

Figure 2: Map of Oregon State Parks

Note: Shown is the U.S. state of Oregon with the location of 44 units in the state park system that are included in our analyses. Cities are labeled and shaded in gray for reference.

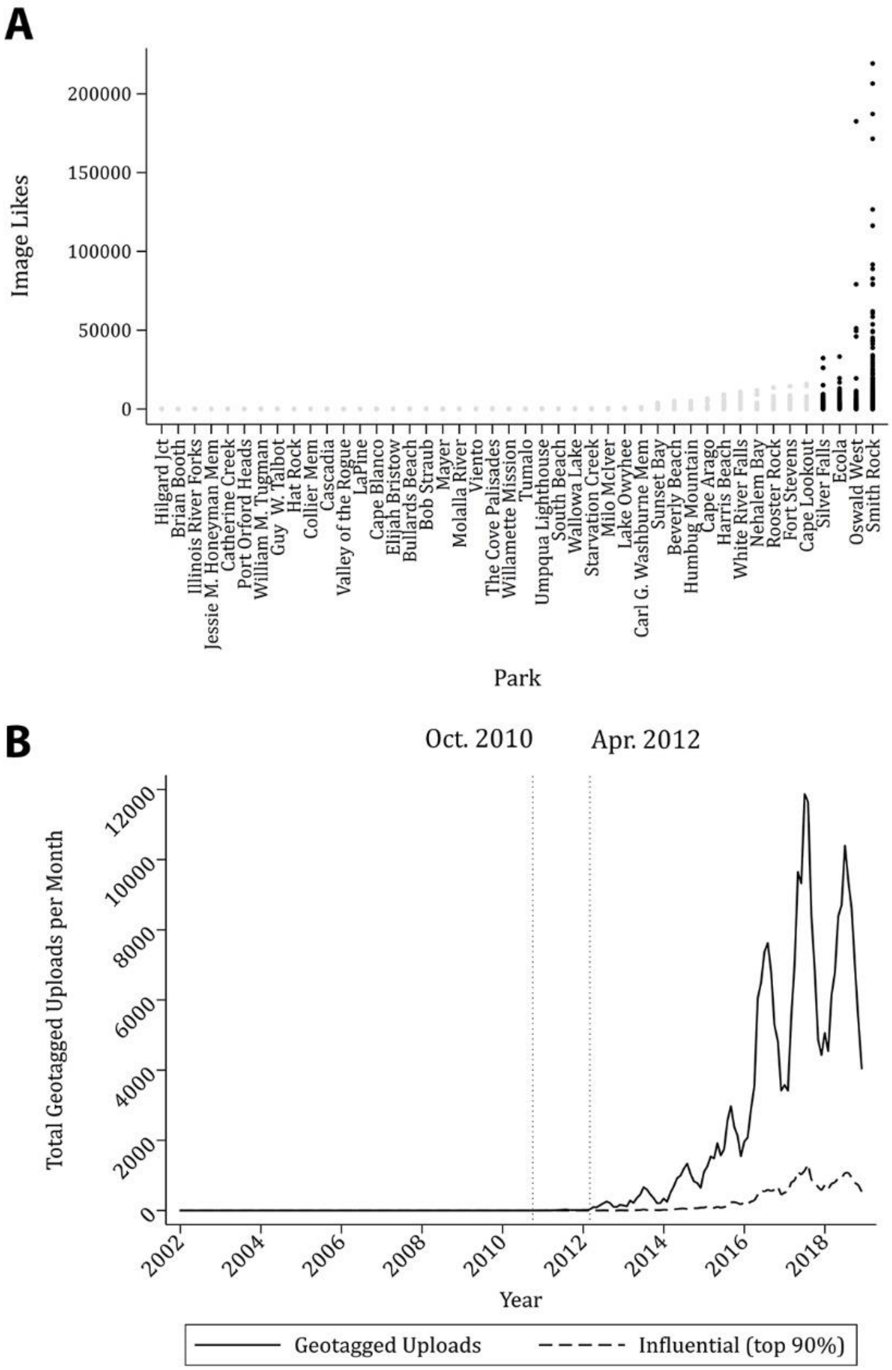

Figure 3: Instagram Engagement by Park and Timing of Geotagging Uploads

Note: Panel (A) plots the Instagram engagement (# of likes) for every image geotagged the 44 parks in our analyses. Gray markers are used for 40 parks with low engagement relative to the 4 high engagement parks (Silver Falls, Ecola, Oswald West, Smith Rock) with black markers. One photo at 1.4 million likes at Smith Rock was removed from this plot to be able to visually compare across parks. Panel (B) displays a plot of geotagged uploads and influential posts in the 90th percentile over time. The first vertical line corresponds to the launch of Instagram in October 2010. The second vertical line corresponds to April 2012, when we begin to see an increase in geotagged uploads for Oregon State Parks. It also is the month where Instagram became available on Android phones, was acquired by Facebook for $1 billion, and reached 50 million monthly active users.

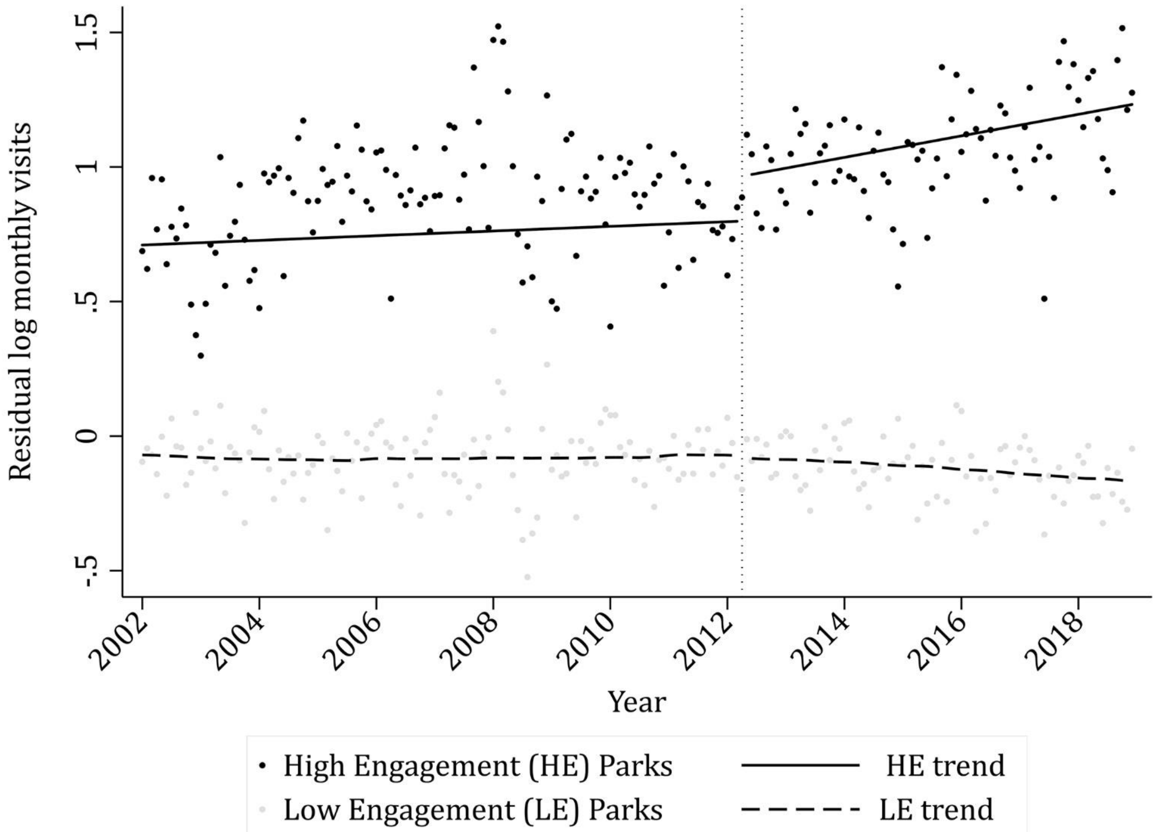

Figure 4: Trends in Visitation by Park-level Instagram Engagement

Note: This figure compares the visitation trends of high Instagram engagement parks to low engagement parks. We first regress log monthly visitation on model covariates and park, quarter, and region by year fixed effects. Next, we separate the residuals by park type and plot them over time with linear trendlines.

Table 1: Descriptive Statistics for 44 Oregon State Park Locations

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
Panel A: Visitation					
Pre Instagram (Jan 2002 - Sep 2010)	4,342	29,862	33,459	30	305,112
Post Instagram (Oct 2010 - Aug 2019)	4,501	33,391	37,670	42	297,668
Panel B: Full Data (Jan 2002 - Aug 2019)					
Visitation	8,843	31,658	35,706	30	305,112
Mean Precipitation	8,843	0.149	0.158	0	1.285
Max Temperature	8,843	60.62	12.05	24.81	97.96
Unemployment Rate	8,843	6.841	2.143	3.300	11.30
Average Housing Price	8,843	221,769	38,889	154,082	299,160
Gas Prices	8,843	2.99	0.742	1.23	4.42
Oregon Population	8,843	3.829e+06	210,180	3.472e+06	4.215e+06
Panel C: High Engagement Parks - Post Instagram Launch (Oct 2010)					
Visitation	426	66,216	48,496	3,874	288,414
Geotags Uploads	426	387.9	629	0	3,845
Influential Posts top 90^{th}	426	50	100	0	573
Cumulative top 90^{th}	426	1,251	2,689	0	13,516
Influential Posts top 95^{th}	426	27	54	0	344
Cumulative top 95^{th}	426	688	1,462	0	7,351
Panel D: Low Engagement Parks - Post Instagram Launch (Oct 2010)					
Visitation	4,075	29,960	34,606	42	297,668
Geotags Uploads	4,075	31	78	0	876
Influential Posts top 90^{th}	4,075	2	7	0	117
Cumulative top 90^{th}	4,075	49	141	0	1,426
Influential Posts top 95^{th}	4,075	1	4	0	71
Cumulative top 95^{th}	4,075	21	71	0	698

Panel E: Park Amenities	N	Amenities[1]	Activity Amenities[2]	Scenery Amenities[3]
High engagement	4	11.8	6.5	2.5
Low engagement	40	11.8	7.5	1.6

Note: High Engagement Parks include Smith Rock, Oswald West, Ecola and Silver Falls. [1] Amenities include bathrooms, vault toilets, dump station, portable water, as well as scenery- & activity-based amenities. [2] Activity amenities include camping, hiking, biking, kayaking, fishing, wind surfing, climbing, surfing, swimming, horses, playground, boat ramp, picnicking, cabin, yurts, yurts with dogs, exhibit information, tepees, amphitheater, disc golf & tours. [3] Scenery amenities are amenities suggesting scenic views and photogenic locations which are listed as viewpoints, beach access, wildlife & waterfalls. Park-specific summary statistics pre- and post-Instagram are shown in Tables A.1 and A.2 in the online Appendix.

Table 2: Results for State Park Visitation Model

Log(Monthly Visits)	(1) Launch of Instagram	(2) Use of Instagram	(3) Interaction Random Effects	(4) Interaction Fixed Effects
IG_Launch	-0.042			
	(0.038)			
IG_Use		0.013	-0.007	-0.007
		(0.040)	(0.039)	(0.039)
High Engagement Parks			1.028***	
			(0.210)	
IG_Use *High Engagement Parks			0.216***	0.216***
			(0.069)	(0.069)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843
R-squared	0.582	0.586		0.588

Note: Panel model include 44 parks in the Oregon State Park system. IG_Launch is equal to 1 for all observations after Instagram's Launch in October 2010. IG_Use is equal to 1 for all observations after April 2012 when Instagram images began being geotagged to Oregon State Parks. There are 4 High Engagement Parks: Smith Rock, Silver Falls, Oswald West, and Ecola. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses. Full model results are displayed in Table A.3 in the Online Appendix.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3: Results for State Park Visitation Model Using Geotagged and Influential Posts

Log(Monthly Visits)	(1) Geotags All	(2) Geotags High/Low	(3) Geotags High/Low + 90%	(4) Geotags High/Low + 95%
IG_Launch	-0.046	-0.048	-0.049	-0.048
	(0.038)	(0.038)	(0.038)	(0.038)
Geotags	0.0002***			
	(6.26e-05)			
Geotags High Parks		0.0002***	8.78e-05*	8.85e-05*
		(5.40e-05)	(4.82e-05)	(4.98e-05)
Geotags Low Parks		0.0003	0.0005	0.0004
		(0.00028)	(0.0003)	(0.0003)
Cum. 90^{th} High Parks			2.80e-05***	
			(6.25e-06)	
Cum. 90^{th} Low Parks			-9.71e-05	
			(0.000156)	
Cum. 95^{th} High Parks				5.14e-05***
				(1.06e-05)
Cum. 95^{th} Low Parks				-0.0002
				(0.0003)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843
R^2	0.587	0.587	0.588	0.588

Note: Panel model include 44 parks in the Oregon State Park system. IG_Launch is equal to 1 for all observations after Instagram's Launch in October 2010. There are 4 High Engagement Parks: Smith Rock, Silver Falls, Oswald West, and Ecola. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses. Full model results are displayed in Table A.4 in the Online Appendix.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. ***** Significant at the 10 percent level.

Supplemental Material for: Ashley Lowe Mackenzie, Steven J. Dundas, Bo Zhao. 2022.
"The Instagram Effect: Is Social Media Influencing Visitation to Public Land."

APPENDIX (For On-line Publication)

The Instagram Effect:
Is Social Media Influencing Visitation to Public Land

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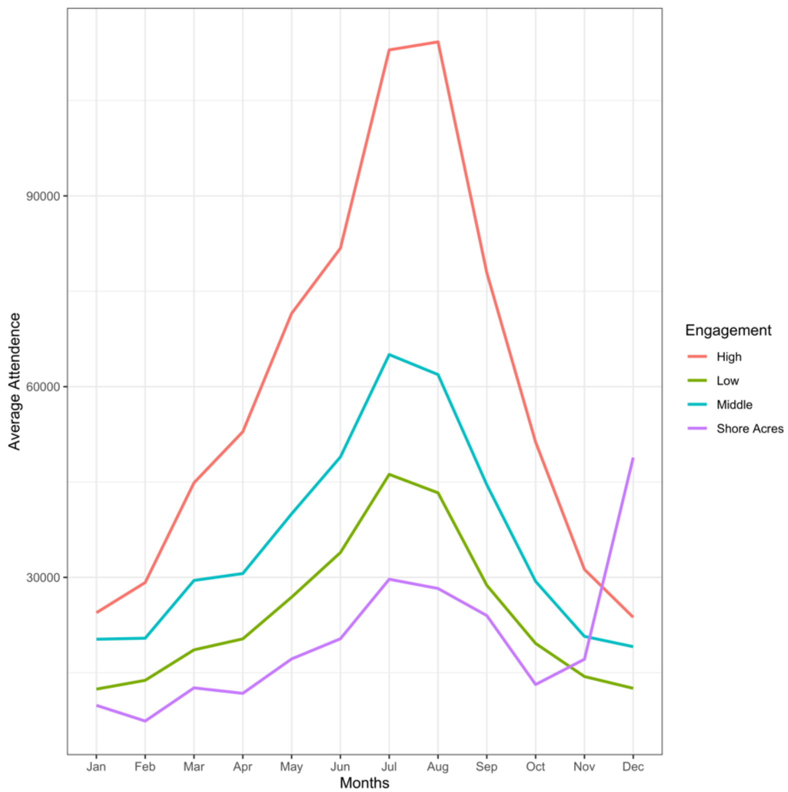
Supplemental Material for: Ashley Lowe Mackenzie, Steven J. Dundas, Bo Zhao. 2022.
"The Instagram Effect: Is Social Media Influencing Visitation to Public Land."

Appendix: Additional Figures and Tables

Figure A.1: Evidence for Removing Shore Acres State Park

Panel A: Average Monthly Visitation



Panel B: Location of Shore Acres Between to Other State Parks

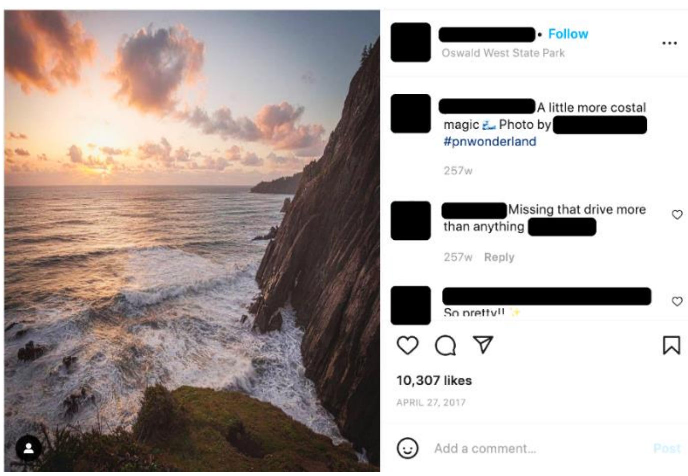
Note: Panel A shows average visits throughout the year for parks with different levels of engagement. The anomaly in visitation patterns to Shore Acres State Park (SP) relative to all other parks is shown in purple, with a large increase in November and December. Panel B shows the location of Shore Acres SP, directly between Sunset Bay SP and Cape Arago SP. The map is from the Oregon Coast Magazine https://www.oregoncoastmagazine.com/2018/02/11/in-her-footsteps/

Figure A.2. Examples of Instagram Geotagged Posts for High-Engagement Parks

Panel A: Smith Rock State Park

Panel B: Silver Falls State Park

Panel C: Ecola State Park



Panel D: Oswald West State Park

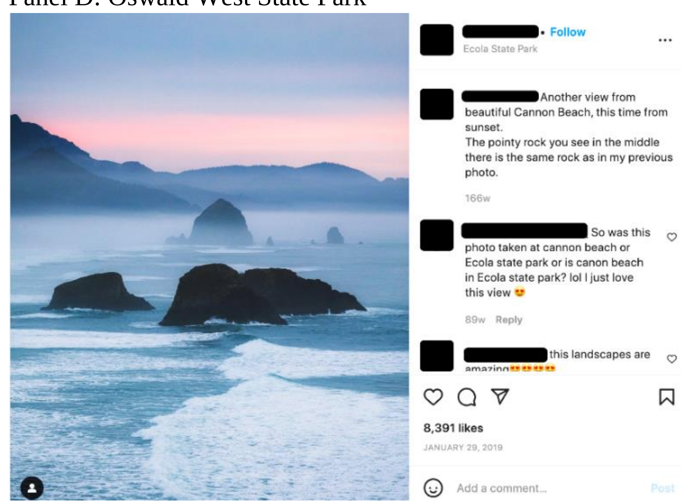
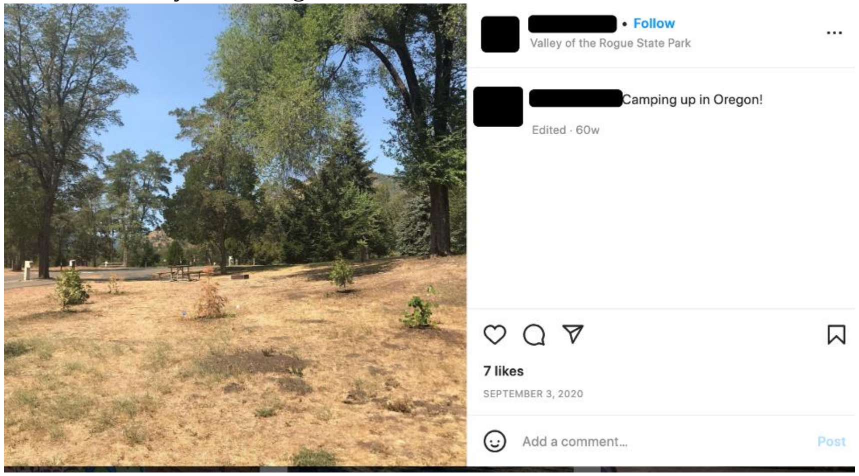


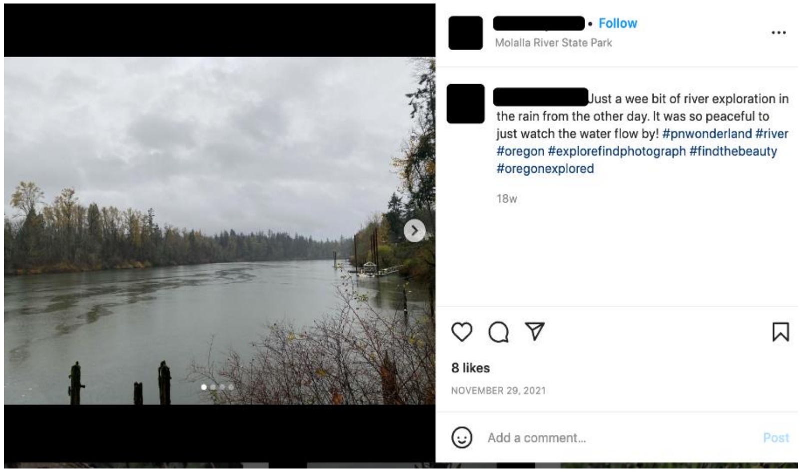
Figure A.3. Examples of Instagram Geotagged Posts for Low Engagement Parks

Panel A: Illinois River Forks State Park

Panel B: Valley of the Rogue State Park



Panel C: Molalla River State Park



Panel D: Brian Booth State Park

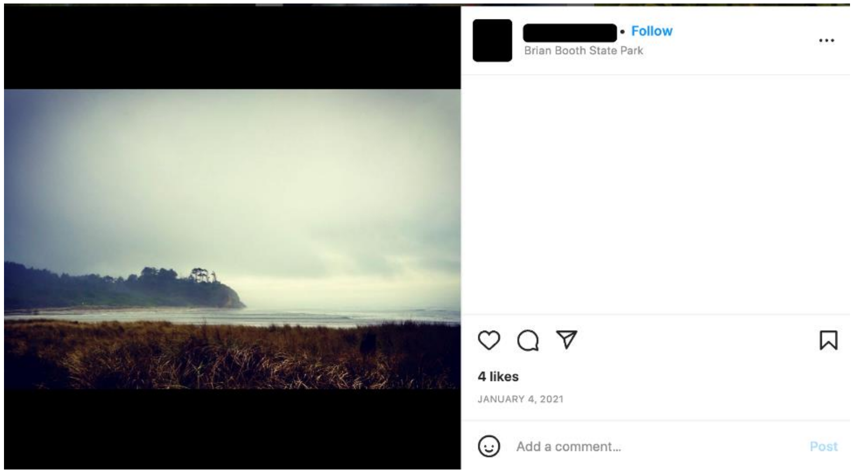
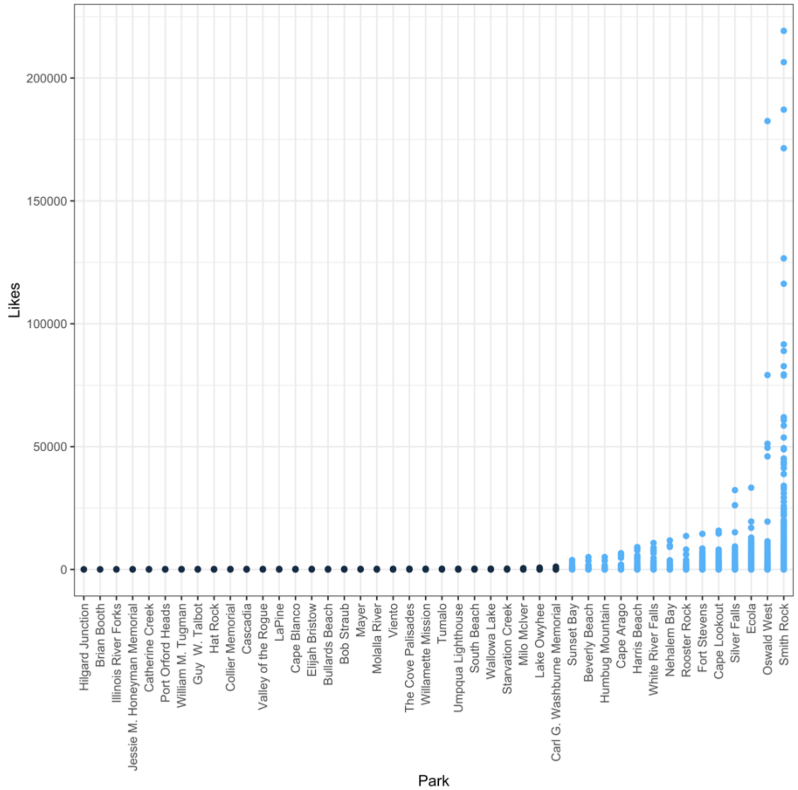
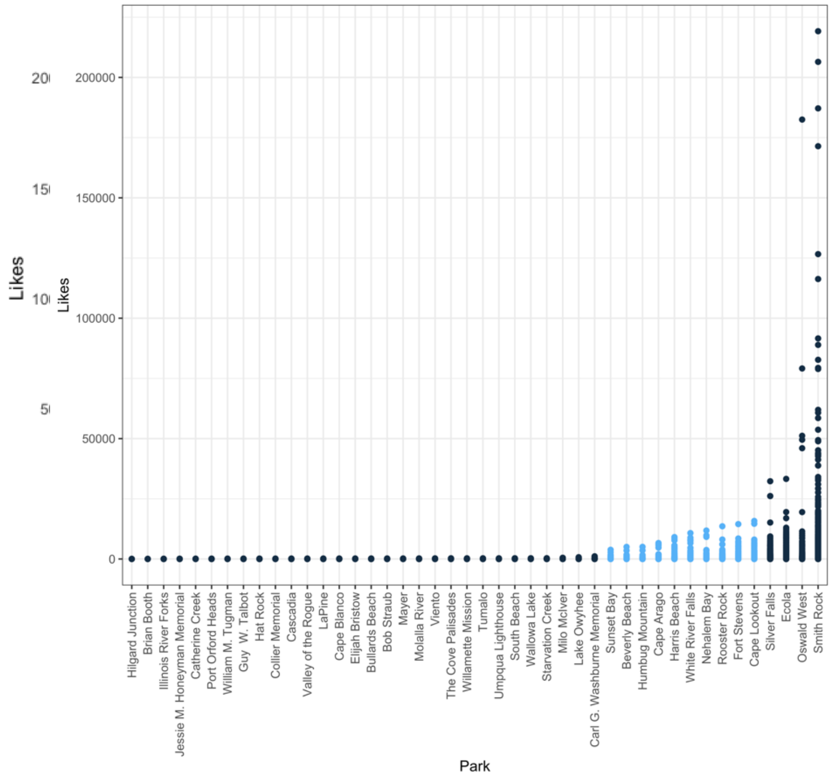


Figure A.4: Instagram Engagement Alternatives

Panel A: High Engagement Top 14 Parks



Panel B: Two Alternatives: Dropping Middle 10, Top 4 Parks



Note: Panel A shows one alternative high engagement park definition using the top 14 parks (in blue). Panel B shows two alternatives: one where the top 4 are compared against the bottom 30 (blue indicates the middle 10 parks that are dropped from the analysis) and another where the top 4 parks are dropped and the high engagement group is defined as the middle 10 parks (in blue).

Table A.1: Pre-Instagram Summary Statistics for Individual Parks

State Park	N	Monthly Visitation	Amenity Count	Scenery Amenities	Activity Amenities
Smith Rock	104	36920	11	2	6
Oswald West	105	53850	7	2	4
Ecola	104	40263	9	3	4
Silver Falls	105	82142	20	3	12
Cape Lookout	80	11753	17	3	9
Fort Stevens	105	75487	22	3	14
Rooster Rock	104	36899	12	1	9
Nehalem Bay	105	19378	22	2	15
White River Falls	70	4856	6	2	3
Harris Beach	104	67001	17	3	10
Cape Arago	104	27713	6	2	3
Humbug Mountain	96	7107	12	2	6
Beverly Beach	104	13815	16	2	10
Sunset Bay	104	57854	17	3	11
Carl G. Washburne	105	18588	11	2	6
Lake Owyhee	61	12983	12	2	6
Milo McIver	104	31581	16	2	9
Starvation Creek	102	16309	8	3	3
Wallowa Lake	104	33446	15	1	10
South Beach	105	54885	17	3	10
Umpqua Lighthouse	100	33397	13	2	8
Tumalo	105	15297	14	0	10
Willamette Mission	101	16190	12	0	10
Cove Palisades	105	46007	16	2	9
Viento	101	6386	10	0	6
Molalla River	104	18974	6	1	4
Mayer	104	14852	9	2	4
Bob Straub	105	11123	6	1	4
Bullards Beach	105	35616	18	3	11
Elijah Bristow	104	11166	8	1	6
Cape Blanco	105	17338	13	3	8
LaPine	99	14618	13	1	8
Valley of the Rogue	105	136272	13	0	9
Cascadia	84	7851	8	1	5
Collier Memorial	103	24285	12	0	8
Hat Rock	105	10896	11	2	8
Guy W. Talbot	104	27996	6	3	3
William M. Tugman	102	16622	15	1	10
Port Orford Heads	105	9454	8	2	5
Catherine Creek	53	2042	6	0	5
Jessie M. Honeyman	102	41007	18	0	13
Illinois River Forks	105	13858	3	0	3
Brian Booth	104	17508	6	2	3
Hilgard Junction	57	11692	6	1	4

Note: Amenities include bathrooms, vault toilets, dump station, portable water, activity-based amenities (camping, hiking, biking, kayaking, fishing, wind surfing, climbing, surfing, swimming, horses, playground, boat ramp, picnicking, cabin, yurts, yurts with dogs, exhibit information, tepees, amphitheater, disc golf & tours) and scenery amenities (viewpoints, beach access, wildlife & waterfalls).

Table A.2: Post-Instagram Summary Statistics for Individual Parks

Park	N	Monthly Visitation	Viral (90th) Posts/Month	Viral (95th) Posts/Month	Maximum Likes	Total Uploads
Smith Rock	107	55,042	126	69	1,477,705	85,452
Oswald West	107	75,718	17	9	182,506	19,104
Ecola	107	42,977	25	15	33,269	28,416
Silver Falls	105	91,601	29	15	32,297	42,389
Cape Lookout	107	11,978	13	7	15,799	24,657
Fort Stevens	107	83,800	9	5	14,495	18,568
Rooster Rock	105	47,691	9	5	13,594	9,618
Nehalem Bay	107	30,812	6	3	11,818	11,941
White River Falls	76	5,798	4	3	10,770	2,792
Harris Beach	107	70,977	6	3	9,106	1,3428
Cape Arago	107	27,729	3	2	6,645	4,611
Humbug Mountain	107	6,103	1	0	5,047	2,565
Beverly Beach	107	17,768	3	1	5,026	4,645
Sunset Bay	107	89,658	3	1	3,830	4,552
Carl G. Washburne	107	26,370	0	0	1,127	1,122
Lake Owyhee	103	7,588	0	0	752	763
Milo McIver	106	35,788	6	3	489	,7535
Starvation Creek	103	16,846	3	1	305	3,620
Wallowa Lake	106	31,762	3	1	295	3,612
South Beach	106	59,307	2	1	289	5,299
Tumalo	107	26,381	2	1	272	4,035
Umpqua Lighthouse	106	23,745	2	1	272	4,035
Willamette Mission	105	14,965	1	0	270	2,830
Cove Palisades	107	33,173	3	0	269	2,074
Viento	103	6,699	1	0	237	1,588
Molalla River	107	24,763	1	0	223	1,901
Mayer	104	20,648	1	0	200	740
Bob Straub	107	10,795	1	0	197	1,299
Bullards Beach	105	34,261	1	0	192	2,121
Elijah Bristow	105	14,864	1	0	189	1,816
Cape Blanco	107	19,375	0	0	184	1,599
LaPine	104	16,263	1	0	179	1,871
Valley of the Rogue	107	145,427	0	0	173	1,424
Cascadia	99	5,698	0	0	172	1,012
Collier Memorial	103	27,889	0	0	159	899
Hat Rock	104	19,387	0	0	157	1,047
Guy W. Talbot	104	33,021	0	0	157	567
William M. Tugman	102	28,227	0	0	146	884
Port Orford Heads	107	10,292	0	0	138	761
Catherine Creek	38	1,755	0	0	123	276
Jessie M. Honeyman	105	34,086	0	0	93	2,562
Illinois River Forks	105	12,948	0	0	93	224
Brian Booth	106	14,392	0	0	56	176
Hilgard Junction	60	10,238	0	0	47	88

Note: Viral posts are defined here as the geotagged uploads to Instagram that reach the 90th and 95th percentiles of engagement on the site. Maximum likes is the amount of "likes" the most popular photo at each park received. Total uploads is the sum of all geotagged uploads on Instagram associated with each park. Amenities are not included here as they did not vary across time.

Table A.3: Full Regression Results for Primary Specifications

Log(Visits)	(1)	(2)	(3)
High Engage		1.028***	
		(0.210)	
IGInf	0.013	-0.007	-0.007
	(0.040)	(0.039)	(0.039)
IGInf *High		0.216***	0.216***
		(0.069)	(0.069)
Temp >90^{o}F	-0.010	-0.010	-0.009
	(0.007)	(0.007)	(0.007)
Temp 80-90^{o}F	-0.002	-0.002	-0.001
	(0.005)	(0.004)	(0.005)
Temp 60-70^{o}F	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)
Temp 50-60^{o}F	-0.011**	-0.010**	-0.011**
	(0.004)	(0.004)	(0.004)
Temp 40-50^{o}F	-0.017***	-0.016***	-0.017***
	(0.004)	(0.004)	(0.004)
Temp 30-40^{o}F	-0.030***	-0.030***	-0.030***
	(0.007)	(0.007)	(0.007)
Temp < 30^{o}F	-0.042***	-0.042***	-0.043***
	(0.012)	(0.011)	(0.012)
PPTmean	-0.181	-0.167	-0.182
	(0.110)	(0.114)	(0.111)
Ln(Gas)	-0.334***	-0.333***	-0.335***
	(0.069)	(0.068)	(0.069)
Ln(pop)	2.041	1.930	2.054
	(5.091)	(5.060)	(5.082)
Unemp. Rate	-0.022	-0.022	-0.022
	(0.019)	(0.019)	(0.019)
Ln(house)	0.157	0.158	0.160
	(0.200)	(0.201)	(0.200)
Year FE	Y	Y	Y
Month FE	Y	Y	Y
N	8,843	8,843	8,843
R^2	0.586		0.588

Note: Panel model include 44 parks in the Oregon State Park system. IGInf is equal to 1 for all observations after April 2012 when Instagram images began being tagged to Oregon State Parks. There are 4 High Engagement Parks: Smith Rock, Silver Falls, Oswald West, and Ecola. Temperature enters the model as a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.4: Full Regression Results for Geotagged and Influential Posts Specifications

Log(Visits)	(1) All Geotags	(2) Geotags High/Low	(3) Geotags High/Low + 90%	(4) Geotags High/Low + 95%
IGLaunch	-0.047	-0.048	-0.049	-0.048
	(0.038)	(0.038)	(0.038)	(0.038)
Geotags	0.0002***			
	(6.26e-05)			
Geotags High		0.0002***	8.78e-05*	8.85e-05*
		(5.40e-05)	(4.82e-05)	(4.98e-05)
Geotags Low		0.0003	0.0005	0.0004
		(0.0003)	(0.0003)	(0.0003)
Cum. 90^{th} High			2.80e-05***	
			(6.25e-06)	
Cum. 90^{th} Low			-9.71e-05	
			(0.0002)	
Cum. 95^{th} High				5.14e-05***
				(1.06e-05)
Cum. 95^{th} Low				-0.0002
				(0.0003)
Temp >90°F	-0.010	-0.010	-0.010	-0.0101
	(0.00733)	(0.00731)	(0.00730)	(0.00731)
Temp 80-90°F	-0.001	-0.00148	-0.00159	-0.00159
	(0.005)	(0.005)	(0.005)	(0.005)
Temp 60-70°F	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Temp 50-60°F	-0.011**	-0.011**	-0.011**	-0.011**
	(0.004)	(0.004)	(0.004)	(0.004)
Temp 40-50°F	-0.017***	-0.017***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
Temp 30-40°F	-0.030***	-0.030***	-0.030***	-0.030***
	(0.007)	(0.007)	(0.007)	(0.007)
Temp < 30°F	-0.042***	-0.042***	-0.042***	-0.042***
	(0.012)	(0.012)	(0.012)	(0.012)
PPTmean	-0.174	-0.172	-0.174	-0.174
	(0.110)	(0.111)	(0.111)	(0.111)
Ln(Gas)	-0.321***	-0.315***	-0.312***	-0.313***
	(0.069)	(0.069)	(0.065)	(0.065)
Ln(pop)	0.156	-0.200	-0.299	-0.288
	(5.035)	(5.035)	(4.929)	(4.894)
Unemp. Rate	-0.022	-0.020	-0.020	-0.020
	(0.019)	(0.019)	(0.019)	(0.019)
Ln(house)	0.104	0.105	0.110	0.108
	(0.196)	(0.195)	(0.193)	(0.192)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843
R^2	0.587	0.587	0.588	0.588

Note: Panel model include 44 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. There are 4 High Engagement Parks: Smith Rock, Silver Falls, Oswald West, and Ecola. Temperature enters the model as a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.5: Results for Social Media Indicators on Visitation to Smith Rock State Park

Log(Visitation)	(1) Smith Rock Baseline	(2) w/ Geotagged Uploads	(3) w. Hashtag Uploads
Geotags		8.07e-05***	
		(2.68e-05)	
Hashtag			4.35e-05
			(4.04e-05)
Temp 90 > °F	-0.021***	-0.022***	-0.021***
	(0.005)	(0.004)	(0.005)
Temp 80-90°F	-0.009	-0.008	-0.009
	(0.006)	(0.006)	(0.006)
Temp 60-70°F	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)
Temp 50-60°F	0.001	0.002	0.001
	(0.005)	(0.005)	(0.004)
Temp 40-50°F	-0.008**	-0.008*	-0.008**
	(0.004)	(0.004)	(0.004)
Temp 30-40°F	-0.015***	-0.017***	-0.016***
	(0.005)	(0.005)	(0.005)
Temp < 30°F	-0.028***	-0.025**	-0.027***
	(0.010)	(0.009)	(0.010)
PPTmean	-0.909	-0.858	-0.821
	(0.790)	(0.774)	(0.765)
Ln(gas)	-0.281	-0.216	-0.268
	(0.183)	(0.185)	(0.184)
IGLaunch	-0.312*	-0.317**	-0.314*
	(0.159)	(0.160)	(0.160)
Year FE	Y	Y	Y
Month FE	Y	Y	Y
Constant	10.42***	10.41***	10.41***
	(0.153)	(0.155)	(0.153)
Observations	211	211	211
R-squared	0.893	0.896	0.894

Note: Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.6: Robustness Check: Main Results with High Engagement as Top 14

Log(Monthly Visits)	(1) Launch of Instagram	(2) Use of Instagram	(3) Interaction Random Effects	(4) Interaction Fixed Effects
IGLaunch	-0.042			
	(0.038)			
IGInf		0.013	-0.035	-0.035
		(0.040)	(0.043)	(0.043)
High Engagement Parks			0.498	
			(0.306)	
IGInf *High Engage			0.147**	0.148**
			(0.060)	(0.060)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843
R-squared	0.586	0.586		0.588

Note: Panel model include 44 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. IGInf is equal to 1 for all observations after April 2012 when Instagram images began being tagged to Oregon State Parks. There are 14 High Engagement Parks in this specification: Smith Rock, Silver Falls, Oswald West, Ecola, Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, and Sunset Bay. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.7: Robustness Check: Geotagged and Influential Posts Results with High Engagement as Top 14

Log(Monthly Visits)	(1) Geotags All	(2) Geotags High/Low	(3) Geotags High/Low + 90%	(4) Geotags High/Low + 95%
IGLaunch	-0.046	-0.049	-0.048	-0.047
	(0.038)	(0.038)	(0.037)	(0.037)
Geotags	0.0002***			
	(6.26e-05)			
Geotags High		0.0002***	0.0001*	0.0001*
		(6.24e-05)	(6.36e-05)	(6.54e-05)
Geotags Low		0.0007	0.0009	0.0007
		(0.0007)	(0.0008)	(0.0008)
Cum. 90^{th} High			2.51e-05***	
			(5.95e-06)	
Cum. 90^{th} Low			-0.0001	
			(0.0004)	
Cum. 95^{th} High				4.63e-05***
				(1.05e-05)
Cum. 95^{th} Low				0.0002
				(0.0005)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843
R^2	0.587	0.587	0.588	0.588

Note: Panel model include 44 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. There are 14 High Engagement Parks in this specification: Smith Rock, Silver Falls, Oswald West, Ecola, Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, and Sunset Bay. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.8: Robustness Check: Main Results with Middle 10 Parks Dropped

Log(Monthly Visits)	(1) Launch of Instagram	(2) Use of Instagram	(3) Interaction Random Effects	(4) Interaction Fixed Effects
IGLaunch	-0.030			
	(0.046)			
IGInf		-0.007	-0.010	-0.037
		(0.050)	(0.055)	(0.048)
High Engagement Parks			1.026***	
			(0.202)	
IGInf *High Engage			0.250***	0.244***
			(0.076)	(0.072)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	6,830	6,830	6,830	6,830
R-squared	0.582	0.582		0.585

Note: Panel model include 34 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. IGInf is equal to 1 for all observations after April 2012 when Instagram images began being tagged to Oregon State Parks. There are 4 High Engagement Parks in this model (Smith Rock, Silver Falls, Oswald West, Ecola) and the next 10 (Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, Sunset Bay) are dropped to compare the top 4 high engagement with the bottom 30 low engagement parks. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.9: Robustness Check: Geotagged and Influential Posts Results with Middle 10 Parks Dropped

Log(Monthly Visits)	(1) Geotags All	(2) Geotags High/Low	(3) Geotags High/Low + 90%	(4) Geotags High/Low + 95%
IGLaunch	-0.034	-0.038	-0.038	-0.037
	(0.046)	(0.045)	(0.045)	(0.045)
Geotags	0.0002***			
	(5.95e-05)			
Geotags High		0.0002***	0.0001*	0.0001*
		(5.81e-05)	(5.16e-05)	(5.29e-05)
Geotags Low		0.0009	0.0012	0.00095
		(0.0008)	(0.00088)	(0.00084)
Cum. 90^{th} High			2.79e-05***	
			(7.27e-06)	
Cum. 90^{th} Low			-0.000181	
			(0.00044)	
Cum. 95^{th} High				5.23e-05***
				(1.18e-05)
Cum. 95^{th} Low				7.84e-05
				(0.00048)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	6,830	6,830	6,830	6,830
R^2	0.584	0.584	0.584	0.584

Note: Panel model include 34 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. There are 4 High Engagement Parks in this model (Smith Rock, Silver Falls, Oswald West, Ecola) and the next 10 (Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, Sunset Bay) are dropped to compare the top 4 high engagement with the bottom 30 low engagement parks. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.10: Robustness Check: Main Results with Top 4 Parks Dropped

Log(Monthly Visits)	(1) Launch of Instagram	(2) Use of Instagram	(3) Interaction Random Effects	(4) Interaction Fixed Effects
IGLaunch	-0.039			
	(0.039)			
IGInf		-0.002	-0.008	-0.029
		(0.041)	(0.061)	(0.046)
High Engagement Parks			0.184	
			(0.332)	
IGInf *High Engage			0.092	0.108
			(0.081)	(0.068)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	7,999	7,999	7,999	7,999
R-squared	0.578	0.578		0.579

Note: Panel model include 40 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. IGInf is equal to 1 for all observations after April 2012 when Instagram images began being tagged to Oregon State Parks. The top 4 High Engagement Parks model (Smith Rock, Silver Falls, Oswald West, Ecola) are dropped from this model and the next 10 (Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, Sunset Bay) are designated as high engagement. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.11: Robustness Check: Geotagged and Influential Posts Results with Top 4 Parks Dropped

Log(Monthly Visits)	(1) Geotags All	(2) Geotags High/Low	(3) Geotags High/Low + 90%	(4) Geotags High/Low + 95%
IGLaunch	-0.044 (0.038)	-0.047 (0.038)	-0.047 (0.038)	-0.047 (0.038)
Geotags	0.0004 (0.0003)			
Geotags High		0.0004 (0.0003)	0.0004 (0.0003)	0.0005 (0.0003)
Geotags Low		0.0011 (0.0007)	0.001 (0.0008)	0.001 (0.0007)
Cum. 90^{th} High			-4.84e-05 (0.0002)	
Cum. 90^{th} Low			-4.13e-05 (0.0004)	
Cum. 95^{th} High				-9.76e-05 (0.0004)
Cum. 95^{th} Low				0.0002 (0.0005)
Economic Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	7,999	7,999	7,999	7,999
R^2	0.579	0.579	0.579	0.579

Note: Panel model include 40 parks in the Oregon State Park system. IGLaunch is equal to 1 for all observations after Instagram's Launch in October 2010. The top 4 High Engagement Parks model (Smith Rock, Silver Falls, Oswald West, Ecola) are dropped from this model and the next 10 (Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverly Beach, Sunset Bay) are designated as high engagement. Economic controls include gas prices, housing prices, unemployment rate, and population. Weather controls include mean monthly precipitation and a non-linear function of daily weather in each month. The panel is unbalanced as there are a few parks that are closed in winter months and a few instances of missing monthly visitation data due to random malfunctions of car counters. Robust standard errors in parentheses.
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.