

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

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ABSTRACT *Public lands in the United States have recently experienced significant increases in visitation. Journalists and park managers suggest Instagram is a primary reason. We explore this issue in the Oregon state park system by combining visitation data with park-specific georeferenced content and engagement indicators from Instagram. Using several empirical specifications, we show suggestive evidence that Instagram is not likely correlated to increased visitation everywhere; rather, it is only in a few locations generating high user participation within the app. We find no contemporary effect and a positive association with cumulative Instagram engagement indicators on visits at this subset of parks.* (JEL Q26, Q56)

1. Introduction

Beginning in the 2000s, there was observable stagnation in visitation to public lands in the United States. Research explored how terrorist attacks (McIntosh and Wilmot 2011; Stevens, More, and Markowski-Lindsay 2014; Bergstrom, Stowers, and Shonkwiler 2020), recessions (Poudyal, Paudel, and Tarrant 2013), or entrance fees (Factor 2007; Stevens, More, and Markowski-Lindsay 2014; Bergstrom, Stowers, and Shonkwiler 2020) affected the overall level of visitation. More recently, visitation has increased and shifted back to pre-1990 trends, and U.S. national parks,

for example, have seen consecutive years of record-high visitation levels (Bergstrom, Stowers, and Shonkwiler 2020). This increase in visitation to public lands produces a tension for state and federal land managers responsible for providing recreation opportunities and preserving wild places (e.g., Mansfield et al. 2008; Jakus et al. 2010; Dundas, von Haefen, and Mansfield 2018).¹ Journalists often blame the growing crowds on public lands on social media photo-sharing apps, most notably Instagram (Figure 1). Park managers attribute social media for 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 these platforms.² To explore the potential interrelationship between the rise of social media and increased visitation to public lands, this article empirically investigates if content and engagement on Instagram has played a role in the recent increase in visits to public lands in the state of Oregon.

We examine 18 years (2002–2019) of visitation data to 44 Oregon state parks paired with newly compiled data on park-specific georeferenced content (i.e., spatially identified) and

¹At the state level, increases in visitation are quickly outpacing budget allocations to maintain recreational facilities and prevent environmental disturbances (Smith, Wilkins, and Leung 2019). Many agencies are working with a significant backlog of deferred maintenance, including the National Park Service (\$11.6 billion; NPS 2018) and the Oregon Parks and Recreation Department (\$59 million; Mukumoto 2019). The concern of negative effects from overuse, stagnating budgets, and staffing levels coupled with aging infrastructure are major concerns facing such agencies.

²See Capital Public Radio's YosemiteLand podcast, episode 1, “Selfie Trap” (n.d.), for more background information: <http://www.capradio.org/news/yosemiteland/2018/07/11/yosemiteland/yosemiteland>.

Figure 1

National and Regional Headlines on the Connection between Social Media and Increasing Visitation to Public Lands

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
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.
- 3.
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

Sources: 1 = Solomon (2017); 2 = Garcia-Navarro (2017); 3 = Alvarez (2018); 4 = Simmonds et al. (2018); 5 = Holson (2018); 6 = Wastradowski (2019).

the level of engagement (i.e., likes and comments) with that content on Instagram. Our goal is to assess the correlation between Instagram features and the observed increase in visitation to Oregon state parks since the early 2010s. We find that, on average, across all parks in our sample, Instagram is likely not a contributing factor to increased visitation. Notably, when we subset state parks into groups based on in-app activity, we find that parks with Instagram content with high user participation are likely to see increases in visits compared with parks with less in-app user activity. To explore this result further, we parameterize Instagram content as the number of geotagged posts at each park per month and engagement as the cumulative set of influential posts per park (i.e., geotagged content in 90th and 95th percentiles of engagement per year). Our preferred specification suggests that there is not a significant contemporaneous effect associated with content uploaded to Instagram each month, but there is a cumulative effect of influential posts on visitation. This latter result suggests influential content may increase visitation up to 4.2% per month. Practically, this increase suggests such content may drive an additional 2,780 vehicles per month (~ 91 per day) to parks with high Instagram activity. Our findings show that specific parks with content that has high levels of Instagram user

activity may see visitation increase attributable to in-app behavior. These parks also tend to have more scenery-based amenities than lower-activity parks, where we did not find an effect of Instagram on visitation. This suggests that any impact Instagram may have on visitation may be limited to areas with picturesque or iconic landscapes, which app users find desirable. Last, we test that spatially identified geotagged posts are the Instagram feature of interest for estimating potential visitation impacts. A model using the park with the highest user activity in our dataset (Smith Rock State Park) shows a significant positive correlation between geotagged content and visitation while suggesting no effects related to park-specific user-generated posts via organizational hashtags.³

The rise of social media presents a potential factor that may influence recreational visits to public lands (Ghermandi and Sinclair 2019; Miller et al. 2019; Wood et al. 2020) but empirically linking in-app behavior from a social media platform to visitation has not

³ A hashtag (#) is a user-generated classification mechanism where individuals place a pound sign in front of an unspaced phrase. The tag enables cross-referencing and searchable content. It allows the platform's algorithm to push the content to other users outside their network who might be interested in the content. YouTube is a video-sharing platform that also uses hashtags to expand viewership, as does the most recent fastest-growing social media platform TikTok.

yet been attempted. Previous work focuses on using social media content to aid in approximating visitation levels and understanding visitor-use patterns (Wood et al. 2013; Sessions et al. 2016; Levin, Lechner, and Brown 2017; Tenkanen et al. 2017; Fisher et al. 2018; Walden-Schreiner, Leung, and Tateosian 2018; Walden-Schreiner et al. 2018; Wilkins, Wood, and Smith 2021) or assessing differences in data quality and usage among platforms (Manikonda, Meduri, and Kam-bhampati 2016; van Zanten et al. 2016; Levin, Lechner, and Brown 2017; Norman and Pickering 2017; Tenkanen et al. 2017; Heikinheimo et al. 2018; Ghermandi and Sinclair 2019; Toivonen et al. 2019). This research is the first to our knowledge to empirically link social media content and engagement as potential drivers of increased visitation to public lands. Importantly, our results suggest that Instagram is not likely to impact visits to all public lands, just specific locations with iconic landscapes that users find favorable and engage with or how the Instagram algorithm delivers such content to users. We also provide evidence that in-app engagement, measured as a cumulative total of influential geotagged content, is a potential Instagram feature that could be associated with some increases in visitation in specific locations. This work contributes to our understanding of how online behavior may translate to changes in visitation to public lands. Our results will help land managers understand and adapt to the emerging social media paradigm and improve stewardship of highly used natural resources. Although our findings are suggestive of a correlation between influential content with high user engagement on Instagram and visitation at specific locations, there may be other social, economic, or demographic trends contributing to increases in people visiting public lands. Our findings indicate that social media content may be one piece of the puzzle in understanding recent changes in outdoor recreation behavior.

2. Social Media and Park Visitation

To explore the connection between social media and park visitation, prior work has focused

on developing visitation estimation methods and tracking visitor-use impacts. The number of geotagged photos posted on social media for a park has been shown to reliably correlate with the number of visitors to a park (Wood et al. 2013; Sessions et al. 2016; Levin, Lechner, and Brown 2017; Tenkanen et al. 2017; Fisher et al. 2018; Wilkins, Wood, and Smith 2021). These findings have important practical applications for reducing the cost of data-gathering across managing agencies and extending visitor-use estimates to wilderness areas where prior data collection was limited (Wood et al. 2013; Fisher et al. 2018; Hausmann et al. 2018; Walden-Schreiner, Leung, and Tateosian 2018; Walden-Schreiner et al. 2018). Data from social media have also helped researchers examine willingness to pay for ecosystem services (Keeler et al. 2015; Ghermandi 2018; Sinclair, Ghermandi, and Sheela 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, Lechner, and Brown 2017; Tenkanen et al. 2017; Walden-Schreiner, Leung, and Tateosian 2018; Walden-Schreiner et al. 2018; Barros, Moya-Gómez, and Gutiérrez 2020). Others have captured imagery in uploaded content and used it to map changes and impact to natural systems and land use (Antoniou et al. 2016; Silva, Barbieri, and Thomer 2018; Toivonen et al. 2019).

There are, however, limitations when using social media data. They do not perfectly substitute for on-site counts of visitors (Wood et al. 2020) and often require researchers to aggregate data across many years (Wilkins, Wood, and Smith 2021). Social media users also are not likely representative of all public land visitors (Wilkins, Wood, and Smith 2021). The accuracy of data from social media used to determine visitation could also be associated with factors such as park popularity, the type of user base of a particular social media platform, and how users engage with the platform (van Zanten et al. 2016; Levin, Lechner, and Brown 2017; Norman and Pickering 2017; Tenkanen et al. 2017; Manikonda, Meduri,

and Kambhampati 2021).⁴ Wilkins, Wood and Smith (2021) provide a systematic review of the relationships between the impact of social media and park visitation. The meta-analysis noted only one article (Hausmann et al. 2017) that uses in-app engagement behavior (i.e., the number of likes content receives) in their analysis. X (Twitter) and Flickr tend to be the most often 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; Wilkins, Wood, and Smith 2021). For Instagram, which has been shown to outperform X and Flickr as a proxy for visitation (Tenkanen et al. 2017), data collection is a bit more challenging owing to recent changes in access to its APIs (Heikinheimo et al. 2018; Ghermandi and Sinclair 2019; Toivonen et al. 2019).

Our research focuses on Instagram because of its large user base (one billion active monthly users) and the direct claims made by journalists linking the app to visitation trends (Figure 1). The two key features of Instagram often mentioned as potential drivers of visits are geotagging (i.e., providing exact spatial coordinates for beautiful scenery) and the ability of content to “go viral” and be viewed by large sets of users.⁵ Instagram was exclusively available for iPhone mobile devices using iOS

⁴For example, Facebook, X (Twitter), and Instagram are in the top five most popular sites on the internet currently but differ in how communities are created and what content is shared among its users. Facebook has the largest number of monthly users and community is built on mutual acceptance of friend requests to access one another’s content. X (Twitter) does not require mutual acceptance if the account is public. The content of X is predominately delivered as tweets, or 280 characters conveying thoughts or ideas, and was the first site that popularized the hashtag. Facebook allows hashtags, but searchable content is difficult given that community is built on mutual friendship acceptance. Instagram also does not require mutual acceptance to see content if the account is public, has searchable user-generated tagging, but differs from X by aiming at primarily sharing visual content with a caption. Readers are referred to Toivonen et al. (2019). for an in-depth breakdown of various social media sites and the general habits of the users.

⁵“Going viral” refers to when an image, video, advertisement, and so on is circulated rapidly on the internet, receiving more engagement from users in the app than normal. Engagement for Instagram are the likes and comments a post receives. There is no predetermined threshold of engagement that qualifies content as going viral.

after its release in October 2010 and grew rapidly from there. It registered one million active users in the first two months, growing to 50 million once it was acquired by Facebook and opened to Android operating systems in April 2012. There are currently more than one billion monthly active users, and it is in the top five most popular websites on the internet as of 2023. The app has features that organize users’ shared content of photos under georeferenced locations (geotags), hashtags (January 2011), an Explore page (June 2012), stories (August 2016), and reels (August 2020).⁶

When Instagram first launched, content was presented chronologically to users. Public users could share content with others outside their network by geotag or hashtag. Each method placed every photo under a searchable URL page containing all other public account users’ content with the same tag.⁷ The Explore page began Instagram’s shift from chronological ordering to an individualized algorithmic curation of content based on the location and behavior of an individual user in the app. Instagram further explored algorithmic ordering in August 2012 with the PhotoMaps feature, which gave users the ability to explore geotagged locations spatially regardless of the time when content was posted to the app. Instagram moved away from PhotoMaps once all of its content became part of its new algorithmic-based searchable system on March 15, 2016. We do not include data for stories or reels here. Stories represent a different type of ephemeral content that disappears within 24 hours of posting to the app, and reels were introduced after the timeframe for our analyses.

Data from Instagram provide an opportunity to quantify content and engagement of place-specific posts and explore how in-app behavior may correlate with outdoor recreation visitation trends. Our hypothesis is that content (i.e., photos) uploaded in a month

⁶Stories are short-lived content typically only visible on a user’s feed for 24 hours unless the user pins it to their profile. Reels are short video clips ranging from 15 seconds to a few minutes.

⁷Profiles posting under a hashtag are organized under www.instagram.com/explore/tags/<hashtag>. Geotag URLs are organized under www.instagram.com/explore/location/<LocationID>.

under geotags or hashtags captures people that have recently visited the location, are sharing memories of the location, or are linking some experience to the location via the tag chosen. Geotags use the GPS coordinates embedded in an uploaded photo and provide a suggested geolocation designated in the app.⁸ Geotags can also be created by a user and used by others. Since geotags are creatable, some “points of interest” locations have multiple geotags and are linkable by the name used and the GPS coordinates associated with the location. Geotagged names are searchable under the Places tab in the app. Geotags and the precise locational information they provide are a primary reason many in the news media are blaming Instagram, rather than other social media platforms, for the influx of visitation.

Each geotagged image in Instagram has elements of engagement from the broader user base. The number of likes and comments each post receives reflects app users who enjoyed the content and provides a measurement of the impact it had on users. Content that has received significantly more engagement than other posts may indicate viral content. Viral content is more actively shown or suggested to other Instagram users and increases the audience for that content. The ability for content to go viral likely increased when Instagram moved from chronological ordering to its current algorithmic-based organizational structure. The mechanisms at play with viral, or influential, content are that a broad set of users are exposed to previously unknown locations for outdoor recreation opportunities or are reminded of a location, which could induce a potential future visit.

Regardless of the mechanism, land managers are responding to both content and engagement on Instagram. In 2018, the Jackson Hole (Wyoming) Travel and Tourism Board began a campaign directed at Instagram influencers, individuals with thousands to millions

of followers who endorse products, places, and lifestyles through the content they share, to stop geotagging photographs with exact locations (Holson 2018). Similar campaigns have appeared endorsing tagging responsibly by swapping location-specific geotags with generic or more ambiguous locations (Merlan 2019; Wastradowski 2019).⁹ Although some groups are attempting to deter visitors because of overcrowding, other tourism boards see opportunities to increase visitation by using Instagram influencers. For example, Travel Oregon launched a “Seven Wonders of Oregon” campaign with a promotional video and the use of Instagram influencers (McOmie 2014), and Utah had a “Mighty 5” ad campaign to increase visitors to its national parks (Drugova, Kim, and Jakus 2021).

3. Data

The Oregon Parks and Recreation Department (OPRD) manages 254 properties and over 100,000 acres of public lands in Oregon as of 2022. We first collected monthly visitor counts and details on available amenities for all properties managed by OPRD from January 2002 to August 2019. Each location has many 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 recreation areas and sites, scenic corridors and viewpoints, natural areas, or heritage sites. The focus of our analysis is on state parks because these units, on average, have more amenities (e.g., developed campgrounds) and may have more reliable visitor counts because of higher staffing levels compared with other unit types. It is also helpful to concentrate our analysis on sites with a similar classification to provide a

⁸Since the acquisition of Instagram by Facebook in 2012, geolocation of posts was enabled through “Facebook places,” points of interests representing the centroid of a known location, such as a shop or a town. Exact locations for geotag photos were shown on PhotoMaps (August 2012–September 2016), which provide searchable geotags on highly personalized maps.

⁹Currently, the Leave No Trace Organization prompts seven principles for minimum impact practices for anyone visiting the outdoors. An eighth principle has been proposed regarding responsible geotagging and is considered an unofficial principle.

common pool of substitutable park locations (Weiler and Seidl 2004; Weiler 2006; Fredman, Friberg, and Emmelin 2007; McIntosh and Wilmot 2011; Poudyal, Paudel, and Tarrant 2013; Stevens, More, and Markowski-Lindsay 2014; Bergstrom, Stowers, and Shonkwiler 2020). Visitor counts at state parks are measured by standard traffic monitoring technology counting individual vehicles placed at entrances to a park and recorded by OPRD staff each month. OPRD estimates visitor counts by assuming the same number of passengers per vehicle (four) at all locations. Given this, and our conversations with OPRD staff, we proceeded with car counts as our dependent variable because adjusting to visitors using OPRD's method is only a rough approximation, and a simple scaling of the car count variable would not change our model outcomes or interpretation of those outcomes.

Although there are 50 state parks, three sites were removed from our dataset at the outset. Two (Bates and Cottonwood Canyon) were new additions to the OPRD system during our study timeframe (January 2002–August 2019) and only existed as state parks after the launch of Instagram. Shore Acres State Park was removed owing to large anomalies in the recorded monthly visitation counts compared with all other parks.¹⁰ This narrows our dataset initially to 47 state parks in Oregon.

A cursory view of the initial visitation data shows that many of these locations experienced an increase in visitors in the 2010s, but visitation at some locations were flat or decreasing (Appendix Figure A2). This suggests that, although overall aggregated trends show increased visitation to public lands, park-specific factors are likely, including social media content and engagement, which are important to consider when estimating visitation models. Park visitation models typically

assume that visits are a function of travel cost, population, seasons, and other economic factors. Higher gas prices increase travel costs and are likely to impact an individuals' budget and recreational decisions. OPRD visitor surveys find most visitors to Oregon state parks live in Oregon (66%), and 65% of visitors travel more than 31 miles to reach a park (Bergerson 2019). Since our population of interest is traveling in the U.S. Pacific Northwest, we use regional conventional gasoline prices from the U.S. West Coast (PADD5) to control for travel costs (Oh and Hammitt 2011; Poudyal, Paudel, and Tarrant 2013; Bergstrom, Stowers, and Shonkwiler 2020).¹¹ Population estimates control for growth in the population of potential recreators (Poudyal, Paudel, and Tarrant 2013; Bergstrom, Stowers, and Shonkwiler 2020). These estimates for Oregon are from the Portland State University Population Research Center, which provides annual population estimates in the years between the national census conducted by the U.S. Census Bureau. We use a linear interpolation to create monthly time steps for this variable. Economic factors commonly used as controls include median income, personal savings, unemployment rate, business cycle index, and consumer confidence index (Oh and Hammitt 2011; Poudyal, Paudel, and Tarrant 2013; Stevens, More, and Markowski-Lindsay 2014; Bergstrom, Stowers, and Shonkwiler 2020). Our focus on a single state would likely benefit from state-specific economic indicators rather than national trends, and it is important to have a temporal match between visitor counts (monthly) and the economic indicators collected (Poudyal, Paudel, and Tarrant 2013). Given prior work that suggests consumer confidence indicators provide a good fit for predicting park visitation (Poudyal, Paudel, and Tarrant 2013), we use Oregon's unemployment rate and Zillow's Housing Value Index for all homes in the state. Both indicators are measured monthly

¹⁰Shore Acres hosts several seasonal events not related to outdoor recreation (e.g., holiday lights show) that cause large variation in month-to-month visitation compared with all other parks, as shown in Appendix Figure A1, panel A. There are also two state parks directly next to Shore Acres (Sunset Bay and Cape Arago; Appendix Figure A1, 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.

¹¹Gas prices are obtained from the U.S. Energy Information Administration, available at <https://www.eia.gov>, which also provides national inflated-adjusted average gasoline prices. Using these national prices instead of regional ones does not change our results.

Figure 2
Map of Oregon State Parks



Note: The map shows the location of 44 units in the Oregon state park system that are included in our analyses. Cities are labeled and shaded gray.

and provide reasonable controls for local economic conditions and consumer confidence.¹²

Outdoor recreation choices are also affected by weather (Dundas and von Haefen 2020), although weather is not often (if at all) included in visitation models. We obtained 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 are 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 in each month separated into 10 temperature bins with intervals set at a 10°F scale ranging from less than 30°F to more than 90°F (e.g., > 30°F, 30°F–39.9°F, 40°F–49.9°F). This binning approach allows us to identify a nonlinear effect

of temperature and how an additional hot or cold day per month affects visitation. Precipitation is controlled for by using the monthly average precipitation in inches.¹³

Instagram Data

We collect data on all content posted to Instagram and geotagged to 44 Oregon state park locations (Figure 2) from the launch of Instagram in October 2010 until August 2019.¹⁴

¹³A 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.

¹⁴The 44 parks 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.

¹²Indicators such as median income and personal saving are estimated only quarterly for Oregon. Our outcomes of interest do not change if quarterly income or savings are included in model specifications.

The geotagged images and metadata are collected from Instagram using a combination of public domain Python scripts.¹⁵ The application gathers information on the tag of interest (geotag or hashtag) and then crawls the URL where Instagram stores all public posts under the tag of interest visible to public Instagram users.¹⁶ A JavaScript Object Notation is produced with information on each post indexed by the date the content was posted, the number of likes and comments each photo received (i.e., engagement), and the photo caption. We do not collect private demographic information on the user from the Instagram bio.¹⁷ When a park had multiple geotag locations associated with it, posts for each separate geotag were collected and linked to the specific park location. During the process of obtaining these data, two parks from the initial 47 were dropped (L. L. “Stub” Stewart and Alfred A. Loeb) owing to Instagram server-side retrieval errors that prevented collection of geotagged images. Prineville Reservoir State Park was also dropped from the analysis because it did not have a park-specific geotag. Of the 44 parks for the analysis, 20 are on the Oregon coast, 11 are within the Willamette Valley or Columbia River Gorge, and 13 are within or east of the Cascade Range.

The collected information allows us to quantify Instagram content and engagement activity related to each state park. We measure content as the number of geotagged uploads for each park per month. We calculated the engagement variable as the cumulative amount of geotagged content (i.e., photos) in our dataset that received significantly more engagement each year than all other content. This cumulative effect captures how much visitation may change in response to a

permanent increase in influential posts for a location. We measure this variable as follows:

$$InfPost_{pT} = \sum_{t=1}^T Content_{pt}^l, \quad [1]$$

where $InfPost_{pT}$ represents the cumulative sum of influential posts at park p in the current month T , and $Content_{pt}^l$ represents the content in each month t that exceeds a threshold l for high engagement. We measure high engagement as the observed number of likes, a tally of the number of users in the app who have interacted with a geotagged photo (i.e., clicked the heart icon in the post). We identify the threshold for high-engagement content as those photos in the 90th and 95th percentiles of likes for all geotagged photos posted in the given year. This characterization identifies content with high engagement that is likely shown to a broad set of users under Instagram’s evolving content delivery algorithm. Selecting content as high engagement per year for this variable is important, as it accounts for potential changes over time to Instagram’s algorithm and general social media trends.¹⁸ A high volume of likes captures a variety of user motivations, such as desirable aesthetic or attractive qualities of the content posted, which could be previously known or unknown to the user viewing the content. These variables representing both content and engagement allow us to test for contemporaneous and cumulative effects of geotagged Instagram posts on visitation.

Our final dataset is a panel comprising 44 parks across 212 months, from January 2002 to August 2019. The panel is slightly unbalanced because a few parks are closed in winter months, and there are a couple of instances where monthly visitation data are missing at a park due to random malfunctions of car counters collecting the information. Table 1, panels A and B, shows aggregate summary statistics for our sample.

¹⁵Richard Arcega’s Instagram Scraper (no longer publicly available), Instaloader, Scrape-Instagram-by-Location (available at <https://github.com/timkiely/scrape-instagram-by-location>).

¹⁶Recent changes made to Instagram’s API policy require 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.

¹⁷An Instagram bio is a 150-character description under the username on an Instagram profile page.

¹⁸We also characterize influential content as the 90th and 95th percentiles of the full set of geotagged photos, rather than by year (see [Appendix Table A3](#)). For our full set of photos, it only takes 135 or 209 likes to be considered in the top 90th and 95th percentiles of photos, respectively.

Table 1
Descriptive Statistics for 44 Oregon State Park Locations

Variable	N (1)	Mean (2)	SD (3)	Min. (4)	Max. (5)
<i>Panel A. Visits per Month</i>					
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
<i>Panel B. Full Data (Jan. 2002–Aug. 2019)</i>					
Visits per month	8,843	31,658	35,706	30	305,112
Mean precipitation (in.)	8,843	0.149	0.158	0	1.285
Max temperature (°F)	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	3,829,000	210,180	3,472,000	4,215,000
<i>Panel C. High-Activity Parks: Post-Instagram Launch (Oct. 2010)</i>					
Visits per month	426	66,216	48,496	3,874	288,414
Geotagged content uploads	426	387.9	629	0	3,845
Influential posts top 90th	426	50	100	0	573
Cumulative top 90th	426	1,237	2,689	0	13,516
Influential posts top 95th	426	27	54	0	344
Cumulative top 95th	426	680	1,462	0	7,351
<i>Panel D. Low-Activity Parks: Post-Instagram Launch (Oct. 2010)</i>					
Visits per month	4,075	29,960	34,606	42	297,668
Geotagged content uploads	4,075	31	78	0	876
Influential posts top 90th	4,075	2	7	0	117
Cumulative top 90th	4,075	47	141	0	1,426
Influential posts top 95th	4,075	1	4	0	71
Cumulative top 95th	4,075	21	71	0	698
<i>Panel E. Park Amenities</i>					
	N	Amenities ^a	Activity Amenities ^b	Scenery Amenities ^c	
High activity	4	11.8	6.5	2.5	
Low activity	40	11.8	7.5	1.6	

Note: High-activity parks include Smith Rock, Oswald West, Ecola, and Silver Falls.

^a These include bathrooms, vault toilets, a dump station, portable water, and scenery- and activity-based amenities.

^b These include camping, hiking, biking, kayaking, fishing, wind surfing, climbing, surfing, swimming, horses, a playground, a boat ramp, picnicking, a cabin, yurts, yurts with dogs, exhibit information, tepees, an amphitheater, disc golf, and tours.

^c These suggest scenic views and photogenic locations that are listed as viewpoints, beach access, wildlife, and waterfalls. Park-specific summary statistics pre- and post-Instagram are shown in [Appendix Tables A1 and A2](#).

Average monthly visitation to these state park units was approximately 31,700 over the nearly 18-year timeframe. Post-Instagram (October 2010–August 2019) visitation was slightly higher (~33,400/month) than pre-Instagram (January 2002–September 2010) visitation (~29,900/month). During the time-frame of the sample, Oregon’s population ranged from 3.47 million to 4.22 million, and the spread of the monthly unemployment rate

was 3.3%–11.3%. Average housing prices (\$154,000–\$299,000) and gas prices (\$1.23–\$4.42/gallon) also had significant monthly variation. Summary statistics for visitation, amenities, and Instagram geotagged posts by park unit are in [Appendix Tables A1 and A2](#). Table 1, panels C–E, shows summary statistics for different grouping of parks based on Instagram user activity that are described in the next section.

4. Estimation Strategy

We start with a simple visitation model, proceed by adding a quasi-experimental research strategy, and then add content and engagement variables from Instagram. The first modeling specification examines the impact of Instagram's launch on visitation using a binary indicator to denote the pre- and post-Instagram periods IG_{Launch_t} :

$$\begin{aligned} \ln(Visits_{pt}) = & \beta_0 + \beta_1 IG_{Launch_t} + \beta_2 T_{pt} \\ & + \beta_3 Prec_{pt} + \beta_3 \ln(Gas_t) + \beta_4 X_t \\ & + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}, \end{aligned} \quad [2]$$

where $Visits_{pt}$ are monthly (t) visits to park p , T_{pt} is a nonlinear 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 conventional gasoline prices from the U.S. West Coast. The vector X_t contains monthly controls for log transformations of population level, unemployment rate, and average housing prices. Our panel data structure allows for a fixed effects specification where we can control for unobservable park-specific characteristics γ_p , and ρ_t and $\tau_{y(t)}$ represent month and year (y) fixed effects, respectively. The estimate of β_1 suggests an average impact of the launch of Instagram on visitation to Oregon state parks.

To improve the specification of our model, the first consideration is the timing of the impact of Instagram on park visitation. Our simple specification in equation [2] assumes that Instagram may have an instantaneous impact on visitation. However, it is not likely that the debut of a smartphone app is an event that would systematically change visitation patterns because Instagram would need time for its user base to grow and develop content. To help determine when Instagram would be likely to start influencing behavior, we plot total geotagged content and influential posts (90th percentile) for all parks over time. In Figure 3a, 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 also coincides with Instagram reaching 50 million active users worldwide, being acquired by Facebook, and releasing the app to Android phone operating systems. It also captures the timing right before Instagram moves from chronological to more algorithmic ordering with the introduction of the Explore page in June 2012. For robustness checks, we also test models on the timing of when Instagram may influence visits, including June 2012, August 2012 (PhotoMaps introduced), and March 2016 (switch to all algorithm-based content). Regardless of the date chosen, the impact of Instagram on visitation is likely better represented by these later dates than the debut of the platform in October 2010. We re-specify equation [2] with IG_{Use_t} as a new indicator variable to account for this timing:

$$\begin{aligned} \ln(Visits_{pt}) = & \beta_0 + \beta_1 IG_{Use_t} + \beta_2 T_{pt} \\ & + \beta_3 Prec_{pt} + \beta_3 \ln(Gas_t) + \beta_4 X_t \\ & + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}. \end{aligned} \quad [3]$$

We consider that there may be significant variation among parks in how visitors and others generate and engage with content in Instagram, as prior work has found that social media activity is associated with park popularity (Tenkanen et al. 2017). To visualize this potential variation, we plot the user activity (number of likes) for every geotagged image associated with each park in our dataset. This indicator is not illustrative of visitation but rather represents activity on the Instagram platform by those viewing the content. Figure 3b shows this information, with parks ordered from lowest to highest level of user activity moving from left to right along the x -axis. The 30 parks on the left of the figure do have some associated user activity on Instagram, but the scale needed to capture the activity for the parks on the right makes it appear to be near zero. Using the information from this graph, we partition the parks into two groups, high activity and low activity, with the hypothesis that there may be systematic

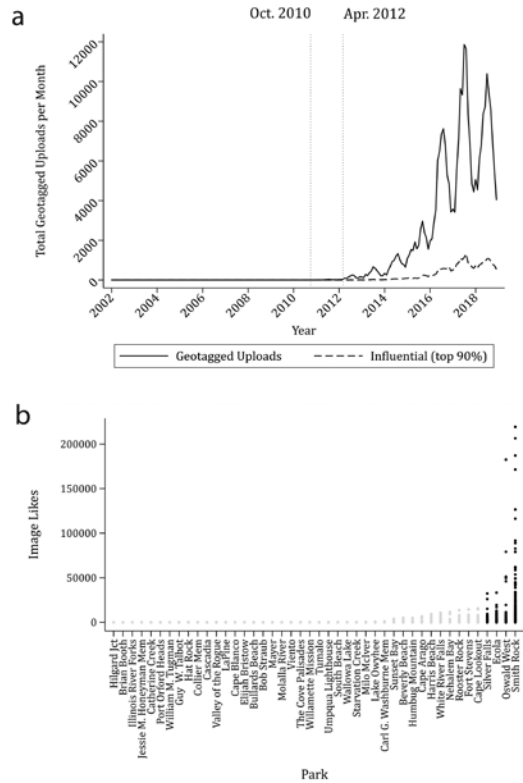
differences in the impact of Instagram on visitation between these park types. Given the natural break after the fourth park starting from the right side of the graph, our preferred designation uses the top four parks, displayed as black dots, as the high-activity group and the remaining 40 parks, displayed with gray dots, as the low-activity group. Importantly, these four parks (Smith Rock, Oswald West, Ecola, and Silver Falls) do not correspond to the top four most visited parks. The most visited park is Valley of the Rogue, which ranks near the bottom in Instagram user activity (for examples of geotagged content posted to Instagram from high- and low-activity parks, please see [Appendix Figures A3 and A4](#)). We check the robustness of our high- and low-activity park definitions through iterations that expand the high-activity parks to the top 14 (the next natural break in Figure 3b), drop the “middle 10” parks to compare the top 4 with the bottom 30, and drop the top 4 and define the “middle 10” as high activity.¹⁹

A comparison of summary statistics for this grouping of parks by user activity is shown in Table 1, panels C–E. We see differences between the groups in terms of Instagram geotagged uploads, with high-activity parks averaging 388 posts and 50 influential (90th percentile) posts per month compared with 31 and 2 per month in low-activity parks. Importantly, the number of available amenities at parks in these groups (panel E) is the same (11.8 on average), with low Instagram activity parks having slightly more activity-based amenities (e.g., hiking, biking, kayaking) and high Instagram activity parks having more scenery-based amenities (e.g., viewpoints). This suggests that high-activity parks may have more “grammable” features.²⁰

While the experimental ideal would expose some parks and not others to Instagram to causally identify the impact on visitation, our

Figure 3

Timing of Instagram Content and Engagement and Activity Levels by Park: (a) Geotagged Content and Influential Posts in the 90th Percentile over Time; (b) Instagram Activity for All Geotagged Content Associated with Analyzed Parks



Note: In the top graph, the dashed vertical lines correspond, respectively, to the launch of Instagram (October 2010) and an increase in geotagged uploads for Oregon state parks (April 2012). In the bottom graph, Instagram activity = number of likes. The gray markers are used for 40 parks with low activity relative to the four high-activity parks (Silver Falls, Ecola, Oswald West, Smith Rock) with black markers. One photo with 1.4 million likes at Smith Rock was removed to maintain a y-axis scale that allows visual comparison across parks.

¹⁹The middle 10 parks are those in gray where the dots begin to appear above the baseline in Figure 3b. These parks are Cape Lookout, Fort Stevens, Rooster Rock, Nehalem Bay, White River Falls, Harris Beach, Cape Arago, Humbug Mountain, Beverley Beach, and Sunset Bay. See [Appendix Figure A5](#) for visualizations of these alternative groupings.

²⁰Urban Dictionary: social media platform-specific adjective relating to Instagram. Something (mostly pictures) is good/fancy/interesting enough to post on Instagram.

grouping strategy has the potential to estimate the impact of Instagram on parks with high user activity relative to those with low activity. By combining our park grouping with an appropriate timing when Instagram content and engagement have the potential to impact visitation, we can estimate a difference-in-differences (DiD) specification of our model. A common assumption needed for consistent estimation of DiD parameters is that the groups being compared have parallel pre-trends. This assumption 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-activity 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 and seasonal and region-by-year fixed effects that are then aggregated by park group and month. The resulting figure suggests parallel trends are a reasonable assumption, and that there may be systematic differences in visitation between high- and low-activity parks after April 2012.²¹

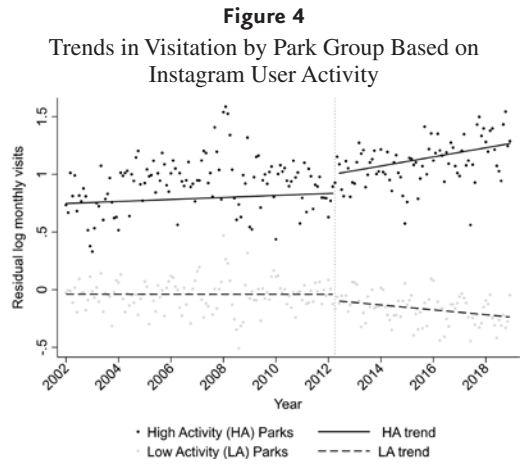
We estimate the DiD specification as follows:

$$\begin{aligned} \ln(\text{Visits}_{pt}) = & \beta_0 + \beta_1(\text{High}_p * IG_{Use_t}) \\ & + \beta_2 IG_{Use_t} + \beta_3 T_{pt} + \beta_4 \text{Prec}_{pt} \\ & + \beta_5 \ln(\text{Gas}_t) + \beta_6 X_t + \rho_t \\ & + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}, \end{aligned} \quad [4]$$

where the interaction term of Instagram’s sustained use ($IG_{Use_t} = 1$ post-April 2012) and an indicator for a high-activity park (High_p) estimates the effect of Instagram on visitation trends at these specific locations. All other variables are the same as defined for equation [2].

Next we specify additional models that use information about the content and engagement in Instagram rather than just the existence of the platform itself. First, we use park-specific Instagram data on content, measured as the sum of geotagged photos for each park per month (Content_{pt}). We include IG_{Launch_t} rather than IG_{Use_t} to differentiate the months where a park received zero geotagged Instagram posts from the time period that had no geotagged

²¹ Parallel trends plots for alternative timing dates (October 2010 Instagram launch; June 2012 Explore page; August 2012 PhotoMaps; and March 2016 algorithm-based content) are in [Appendix Figure A6](#). These additional figures suggest no effect associated with Instagram’s launch in 2010 or algorithm change in 2016 and shows similar trends in June and August 2012 compared with April 2012. This suggests that an event timing in 2012 is probably a reasonable choice for this model specification.



posts because Instagram did not yet exist. We specify this model as follows:

$$\begin{aligned} \ln(\text{Visits}_{pt}) = & \beta_0 + \beta_1 IG_{Launch_t} + \beta_2 \text{Content}_{pt} \\ & + \beta_3 T_{pt} + \beta_4 \text{Prec}_{pt} + \beta_5 \ln(\text{Gas}_t) \\ & + \beta_6 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}. \end{aligned} \quad [5]$$

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

$$\begin{aligned} \ln(\text{Visits}_{pt}) = & \beta_0 + \beta_1 IG_{Launch_t} \\ & + \beta_2 (\text{Content}_{pt} * \text{High}_p) \\ & + \beta_3 (\text{Content}_{pt} * \text{Low}_p) + \beta_4 T_{pt} \\ & + \beta_5 \text{Prec}_{pt} + \beta_6 \ln(\text{Gas}_t) \\ & + \beta_7 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}, \end{aligned} \quad [6]$$

where Low_p is an indicator variable defining low-activity parks. The next iteration of this model adds our engagement variable, measured as the cumulative count of posts with the number of likes in the 90th and 95th percentiles of all content (equation [1]). This disentangles the contemporaneous effect of content volume from the possible cumulative influence of engagement with influential posts (InfPost_{pT}) that can remain visible on Instagram from many months after posting. The next model is specified as follows:

Table 2
Results for State Park Visitation Models

Log(Monthly Visits)	Instagram Launch (1)	Instagram Use (2)	Difference-in-Differences (3)
Instagram launch (Oct. 2010)	-0.042 (0.038)		
Instagram sustained use (Apr. 2012)		0.013 (0.040)	-0.007 (0.039)
Instagram use × high-activity parks			0.216*** (0.069)
Economic controls	Y	Y	Y
Weather controls	Y	Y	Y
Year fixed effects	Y	Y	Y
Month fixed effects	Y	Y	Y
N	8,843	8,843	8,843
R-squared	0.582	0.586	0.588

Note: The panel model includes 44 parks in the Oregon state park system. Instagram launch = 1 for all observations after its launch in October 2010. Instagram use = 1 for all observations after April 2012 when Instagram images began being geotagged to Oregon state parks. The difference-in-differences approach separates parks into high Instagram activity and low Instagram activity. There are four high-activity parks: Smith Rock, Silver Falls, Oswald West, and Ecola. All specifications include the economic controls of gas prices, housing prices, unemployment rate, and population levels. Weather controls include mean monthly precipitation and a nonlinear function of daily weather in each month. The panel is unbalanced, as there are a few parks that are closed in winter and a few cases of missing monthly visitation data owing to random malfunctions of car counters. Robust standard errors are in parentheses. The full model results are in [Appendix Table A4](#).

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

$$\begin{aligned}
 \ln(Visits_{pt}) = & \beta_0 + \beta_1 IG_{Launch_t} \\
 & + \beta_2 (Content_{pt} * High_p) \\
 & + \beta_3 (Content_{pt} \times Low_p) \\
 & + \beta_4 (InfPost_{pT} \times High_p) \\
 & + \beta_5 (InfPost_{pT} * Low_p) + \beta_6 T_{pt} \\
 & + \beta_7 Prec_{pt} + \beta_8 \ln(Gas_t) \\
 & + \beta_9 X_t + \rho_t + \tau_{y(t)} + \gamma_p + \varepsilon_{pt}. \quad [7]
 \end{aligned}$$

$$\begin{aligned}
 \ln(Visits_t) = & \beta_0 + \beta_1 Tags_t + \beta_2 T_t + \beta_3 Prec_t \\
 & + \beta_4 \ln(Gas_t) + \rho_t + \tau_{y(t)} + \varepsilon_t, \quad [8]
 \end{aligned}$$

where $Tags_t$ represents a monthly content count of photos uploaded under either hashtags or geotags, and ρ_t is a month fixed effect. All models are estimated with robust standard errors.

5. Results

Last, we use data from the park with the highest Instagram activity (Smith Rock State Park [SRSP]) to explore a more nuanced understanding the relationship between Instagram content and visitation. We collect content from SRSP related to hashtags to compare this type of information to geotagged content. As noted, geotags provide specific georeferenced locations, while hashtags provide the user with the name of the location along with other descriptive information (but not necessarily geolocation information). We focus this final model on determining the effect of each type of tagging of content on visitations:

Columns (1) and (2) in Table 2 show coefficients from estimating equations [2] and [3] based on the launch of Instagram (October 2010) and when observable use of Instagram begins (April 2012; Figure 3a), respectively. Both models find no significant effect associated with Instagram. In these models, other variables behave as expected. For example, higher gas prices are likely to reduce visitation, and the temperature response function follows an inverted U-shape, suggesting that both high and low temperatures may decrease visitation, which is similar to results in

Dundas and von Haefen (2020). (See [Appendix Table A4](#) for full model results.)

The null result in column (1) suggests that the simple debut of a smartphone app is not an event that would systematically change visitation patterns owing to the time it takes for the app to be incorporated into a user's life and influence their behavior. The result in column (2) suggests that even after Instagram began seeing significant use, there was no significant impact on visitation, on average, across all state parks. The hypothesis that any impact Instagram may have is likely to be heterogeneous across locations leads to the DiD specification in column (3). The results from estimating equation [4] find that high-activity parks experience significantly more visitation associated with Instagram than low-activity parks.²² The coefficient estimate suggests that high-activity parks have experienced a 24.1% increase in visitation relative to low-activity parks since April 2012.²³

This first set of results includes a simple indicator variable for a time when Instagram content specific to Oregon state parks began increasing. Given the potential correlations between the timing of Instagram's increasing content and user base with other similar trends occurring across social media platforms (X, Facebook) and the general overall increase in visitation observed in the 2010s, we next incorporate content and engagement variables to better understand the potential visitation impacts from Instagram. The effect of the contemporaneous count of geotagged uploads (i.e., content) for each park per month shows a positive association with visitation (Table 3, column (1)). The coefficient estimate suggests a marginally significant effect per geotagged image of 0.02%, which translates to a 1.3% increase in visitation each

month associated with contemporaneous Instagram content.²⁴

Our results from the initial modeling suggest visitation impacts may be heterogeneous across parks, as shown in Table 2, columns (3) and (4). To test this, we separate our content variable by high- and low-activity parks (Table 3, column (2)), which suggests that the impact of geotagged content is only significant in high-activity parks with a similar coefficient estimate. However, in this case, a 0.02% increase per geotag translates to a total increase in visits to high-activity parks of 7.8%. This finding supports results from Table 2 that Instagram content is not likely impacting visitation to all parks but visits to specific parks with iconic landscapes that may drive user activity.

Next we add the cumulative effect of influential content with high numbers of likes (i.e., engagement) for our two sets of grouped parks to the model. Columns (3) and (4) in Table 3 show results when we include the cumulative effect of photos that received enough likes to reach the top 90th and 95th percentiles of the full set of geotagged content in our sample. Columns (5) and (6) estimate the same model but with influential content quantified by all content posted in each given year. Once again, we find that the only significant impacts are associated with content and influential posts from high-activity parks. In columns (3) and (4), the content variable remains marginally significant and suggests a contemporaneous increase in visits of 3.4%. This is less than half of the contemporaneous effect captured in the previous model that excludes the engagement variables (Table 3, column (2)). The cumulative effect of influential posts from high-activity parks in the 90th and 95th percentiles is, on average, associated with a 3.5% increase in visitation per month from all current and past influential photos.²⁵ Moving to our preferred specifications that measure influential posts relative to all content posted

²²A Hausman test determined a fixed effects model is preferred over a random effects specification. Nonetheless, when we estimate a random effects model, the coefficient on the interaction of $\ll Eqn001.eps \gg$ is nearly identical to the results in Table 2, column (3).

²³Percentage effects reported include an adjustment to the coefficient to interpret a dummy variable in a semi-log equation (e.g., Halvorsen and Palmquist 1980).

²⁴Average geotagged uploads post-Instagram to all parks is 63 posts per month.

²⁵See 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, columns (3) and (4).

Table 3
Results for Visitation Models Using Instagram Content and Engagement

	Content (1)	Content: High / Low (2)	Content: High / Low + Engagement (90%) (3)	Content: High / Low + Engagement (95%) (4)	Content: High / Low + Engagement by Year (90%) (5)	Content: High / Low + Engagement by Year (95%) (6)
Instagram launch	-0.046 (0.038)	-0.048 (0.038)	-0.049 (0.038)	-0.048 (0.038)	-0.048 (0.038)	-0.048 (0.038)
Content variable						
No. geotags	0.0002*** (6.26e-05)					
No. geotags high-activity parks		0.0002*** (5.40e-05)	0.00009* (4.81e-05)	0.00009* (5.01e-05)	0.00008 (4.67e-05)	0.00008 (4.90e-05)
No. geotags low-activity parks		0.0003 (0.0003)	0.0005 (0.0003)	0.0005 (0.0003)	0.0004 (0.0003)	0.0005 (0.0003)
Engagement variable						
Cumulative nos. 90th percentile (high-activity parks)			0.00003*** (6.33e-06)		0.00003*** (7.33e-06)	
Cumulative nos. 90th percentile (low-activity parks)			-0.0001 (0.0002)		-0.00006 (0.0002)	
Cumulative nos. 95th percentile (high-activity parks)				0.00005*** (1.06e-05)		0.00006*** (1.23e-05)
Cumulative nos. 90th percentile posts (low-activity parks)				-0.0002 (0.0003)		-0.0002 (0.0004)
Economic controls	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Month fixed effects	Y	Y	Y	Y	Y	Y
N	8,843	8,843	8,843	8,843	8,843	8,843
R-squared	0.587	0.587	0.588	0.588	0.588	0.588

Note: The panel model includes 44 parks in the Oregon state park system. Instagram launch = 1 for all observations after its launch in October 2010. There are four high-activity parks: Smith Rock, Silver Falls, Oswald West, and Ecola. Economic controls include gas prices, housing prices, unemployment rate, and population levels. The cumulative number of 90th and 95th posts (columns (3) and (4)) are designated by the likes received (135 and 209 likes) on the entire set of geotagged photos. The cumulative number of 90th and 95th by year (columns (5) and (6)) are designated by likes on set of geotags per year (online [Appendix Table A3](#)). Weather controls include mean monthly precipitation and a nonlinear function of daily weather in each month. The panel is unbalanced, as there are a few parks that are closed in winter and a few cases of missing monthly visitation data owing to random malfunctions of car counters. Robust standard errors are in parentheses. The full model results are in [Appendix Table A5](#).

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

in that year (columns (5) and (6)), we find the contemporaneous effect of content is no longer significant, and the cumulative effect of influential posts suggests an increase in visitation by 4%–4.2% per month from all current and past influential photos (see [Appendix Table A5](#) for full model results). The significance of the cumulative effect suggests that the overall impact of continual online exposure of specific parks with iconic landscapes is associated with a slight increase in visitation over the past decade. The results also highlight how not all public lands are

created equal, and many may not have qualities or attributes that create visible content and engagement on Instagram. In our study area, both park types have the same available amenities to recreators on average. The parks where we can estimate a positive association between Instagram activity and visitation differ in having at least one more scenery-based amenity and fewer available activity amenities compared with the low-activity parks.

Last, we test the differences between content tagged with locational information (geotags) versus organizational information

(hashtags) in SRSP. Data on content tagged with a hashtag for SRSP (#smithrock) allow for an opportunity to investigate another potential tagging feature of Instagram that may influence visitation. SRSP is not the most visited park but is the park with the most user activity and influential photos (see Figure 3b) and a highly photogenic location with a variety of recreational opportunities (i.e., hiking, camping, rock climbing). In our estimation of equation [8], geotagged content significantly and positively correlates with overall visitation, whereas hashtags do not (full results available in online [Appendix Table A6](#)). These results suggest that the provision of locational information may be a potential mechanism driving increased visitation from social media posts. Geotagged photos provide specific information to potential visitors (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 a photo. In other words, hashtags encompass abstract organizational patterns when compared with the specific information provision of georeferenced location tags.

Robustness Checks

To test the robustness of our main findings, we alter the definition of high- and low-activity parks and the timing of Instagram's potential influence. First, we examine alternative definitions of our high-activity parks. We move the high classification to the next clear visible break in Figure 3b to include 10 more parks ([Appendix Figure A5](#), panel A). We then reestimate all our models with this new definition of high activity. Results from estimating equation [4] suggest a 16% increase in visitation to high-engagement parks. This result is less in magnitude than our primary specification (24.1%) and is estimated with less precision ([Appendix Table A7](#)). All models that add content and engagement variables yield similar results to our main specifications with high activity defined as the top four parks ([Appendix Table A8](#)). Is the addition of those 10 parks simply attenuating the impact of the top four or does it suggest that

Instagram may impact visits to more parks? To investigate, we next specify models where the middle 10 are dropped from the analysis ([Appendix Figure A5](#), panel B), so the models compare the original top four to the bottom 30 low-activity parks. These results suggest a slightly higher 27.6% increase ([Appendix Table A9](#)) and a similar result for content and engagement to our primary models ([Appendix Table A10](#)). Last, when we drop the top four and treat the middle 10 as high activity ([Appendix Figure A5](#), panel B), we find no significant effects in the DiD specification ([Appendix Table A11](#)) or the models with content and engagement ([Appendix Table A12](#)). The combination of these results suggests that the potential effect of Instagram on visitation is likely limited to a few parks with very high activity in the app and supports our primary modeling specifications.

We also explore variations in timing of the potential impact of Instagram's various features and algorithmic changes and how it may affect our main results presented in Table 2 ([Appendix Table A13](#)). Important dates include October 2010 (Instagram launch), June 2012 (Explore page), August 2012 (PhotoMaps), and March 2016 (algorithm-based content). All timing specifications show significant results for high-activity parks only. These findings support our preferred specification but also suggest the timing of potential impacts from Instagram may be difficult to pin down to a single point in time.

6. Discussion

This article quantifies whether Instagram has played a part in the observable increase in visitation to state parks in Oregon in the past decade. Although our initial models suggest no overall effect, we find that the introduction of Instagram correlates with increases in visitation to certain Oregon state parks that have high user activity in the app. We present additional specifications that find suggestive evidence of a connection between georeferenced content and influential posts on Instagram and overall visitation. Georeferenced content suggests a 7.8% increase in visitation to high-activity parks. Importantly, when we

add cumulative influential posts to the model, we find the contemporaneous effect of content is no longer significant, and the estimated effect of influential posts suggests an increase in visitation by 4%–4.2% per month from all current and past influential photos. These findings suggest the impact was isolated to certain parks generating high user activity in Instagram and was mostly driven by the influential content at these locations receiving high user engagement in the app. The one observable difference between high- and low-activity parks suggests that scenery-based amenities may play a role. The photogenic qualities of the high-activity parks could be attracting Instagram users for their grammable iconic viewpoints and landscapes (Appendix Figure A3).

There are several potential mechanisms that could explain the estimated effects found here. One avenue may be that a reduction in search and information costs (e.g., Stigler 1961) makes recreators aware of beautiful locations or entices new recreators to start visiting public lands. Smartphone technologies have embedded GPS functions, which enable the relatively costless discovery of new recreation locations, and social media has provided a platform for people to share their experiences, discoveries, and location information more freely among a wider audience. However, if reduced information costs were the sole mechanism, we may expect to see impacts at all locations rather than just a small subset. Another potential mechanism is the bandwagon effect (or herd behavior), in which an individual's demand for a commodity is increased because 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, Wu, and Li 2019; Pan, Rasouli, and Timmermans 2021; Boto-García and Baños-Pino 2022), and political science (e.g., Barnfield 2020). In this case, social media users would see others in these picturesque landscapes and choose to go there to not miss out on the experience or to take a similar photo. Although this research cannot determine the mechanism, it remains a viable area for future work.

Our findings suggest the anecdotal claims that Instagram is a factor in the recent increase

in visitation to public lands may have some validity. However, the act of uploading georeferenced content is not solely responsible for the rapid increase in visitation, as some campaigns have claimed. Our models found that geotagged content at most parks had little to no significant effect. Instagram's geotagging feature provides accessible, low-cost, park-specific information to potential visitors, but it is not the only social media site providing such information. Websites and other social media platforms (e.g., YouTube, TikTok, AllTrails, Gaia, X) provide spatially explicit information for potential recreators. Recent popularity in alternative lifestyles such as #vanlife, a nomadic living situation often involving overnighting in public lands, are other potential mechanisms that may have impacted visitation trends (Monroe 2017).

Overall, the increasing accessibility through information and sharing experiences in outdoor recreation can introduce more people to find appreciation for public lands. Protecting these areas for the benefit of current and future generations is an important role entrusted to public land managers. Tensions arise when visitors, knowingly or unknowingly, negatively impact these public spaces. Instagram influencers have been blamed for ignoring signs in protected, sensitive habitats and not practicing Leave No Trace (LNT) principles to get a grammable image (Canon 2019). Some influencers have experienced legal consequences from the National Park Service when they have shared evidence online of their responsibility for resource degradation (Schaffer 2015). Public shaming campaigns have emerged to place pressure on ending the use of geotagging (Merlan 2019). In Deschutes County, Oregon (home of SRSP) the "Tag Responsibly, Keep Bend Beautiful" campaign focuses on getting outdoor recreators to not reveal location-specific information on social media by using a generic location instead (Wastradowski 2019). Despite these goals, antigeotagging campaigns have been accused of gatekeeping by suppressing low-cost spatial information to limit public land access to potential new recreators (Mullen 2020; Slepian 2021).

From a policy perspective, our results support the idea of investing in a social media

presence for land managers. An online presence can act as an informational pathway to connect with recreational users through education and to potentially mitigate negative outcomes before they occur. Content focusing on best recreational practices, LNT principles, site-specific location updates on resource closures, and safe practices for viewing wildlife or trail information may be helpful in combating misuse in the parks they manage. However, the impact is likely dependent on the ability to generate content that would engage users enough to reach a wider audience on social media. Agencies' awareness and engagement in online communities could also help them prepare for visitation surges. Identifying abnormally high activity and engagement online (i.e., going viral) for content geotagged to their units might be indicative of current and future visitation trends. Public land managers may want to consider commercial filming and still photography permits for media captured in their boundaries, particularly at locations with sensitive resources (e.g., alpine wildflower meadows). Currently, this practice is being used by the National Park Service, which considers commercial filming to include all film, electronic, magnetic, digital, or other recording of a moving image by a person, business, or other entity for a market audience with the intent of generating income, which includes posting footage on social media sites (NPS 2022).

Another potential policy takeaway shows a path for social media companies to improve their public relations. Many of the most popular social media companies rely on advertising revenue to keep their platform free for their users. Data collected on the users of these platforms provide an opportunity for hypertargeted advertising.²⁶ The platforms then provide a path for the user to become an influencer and monetize their account. A potential issue arises when influential or viral geotagged content may impact public land use. It generates a conflict between those generating the impact (social media platforms) and those managing the parks (land managers). Overcrowding can cause environmental

degradation, while exposure to underused parks could help balance use. Unfortunately, the pathway for public agencies and researchers to request online data from leading social media companies on historical and current engagement generated under a public land geotag location is currently unaccommodating.²⁷

In this article, content and engagement data were obtained through a computationally intensive Python script that took many weeks to collect and is increasingly challenging, given Instagram's API permissions. Providing a path to request historical and current de-identified information would be a public service for park managers and researchers examining land use and recreational concerns in public spaces. Other helpful actions for management agencies could include notification services when verified public user accounts post under a publicly managed geotag location. Verified public user accounts, as well as influencers, tend to have large audiences, which can increase the probability that uploaded content will be seen by many people and potentially impact future visitation levels.

This article discusses the complex linkages between social media and visitation to public lands. Future research using surveys is likely needed to solidify the link between the timing of learning or being reminded of a specific location and then actually taking a trip to better understand how social media may be inducing new individuals to participate in outdoor recreation activities. 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.

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²⁶“Hypertargeting” refers to the ability to deliver advertising content to specific interest-based segments in a network.

²⁷Prior to our data collection in 2019, the authors requested data from Facebook, now known as Meta, and never received a response. During the review process Meta has added data request methods such as CrowdTangle and Data for Good; however, the list of prioritized research topics is limited.

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