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The Weekend Effect in Online Reviews

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Data availability statements

The data that support the findings of this article are publicly available on JMR's Dataverse.

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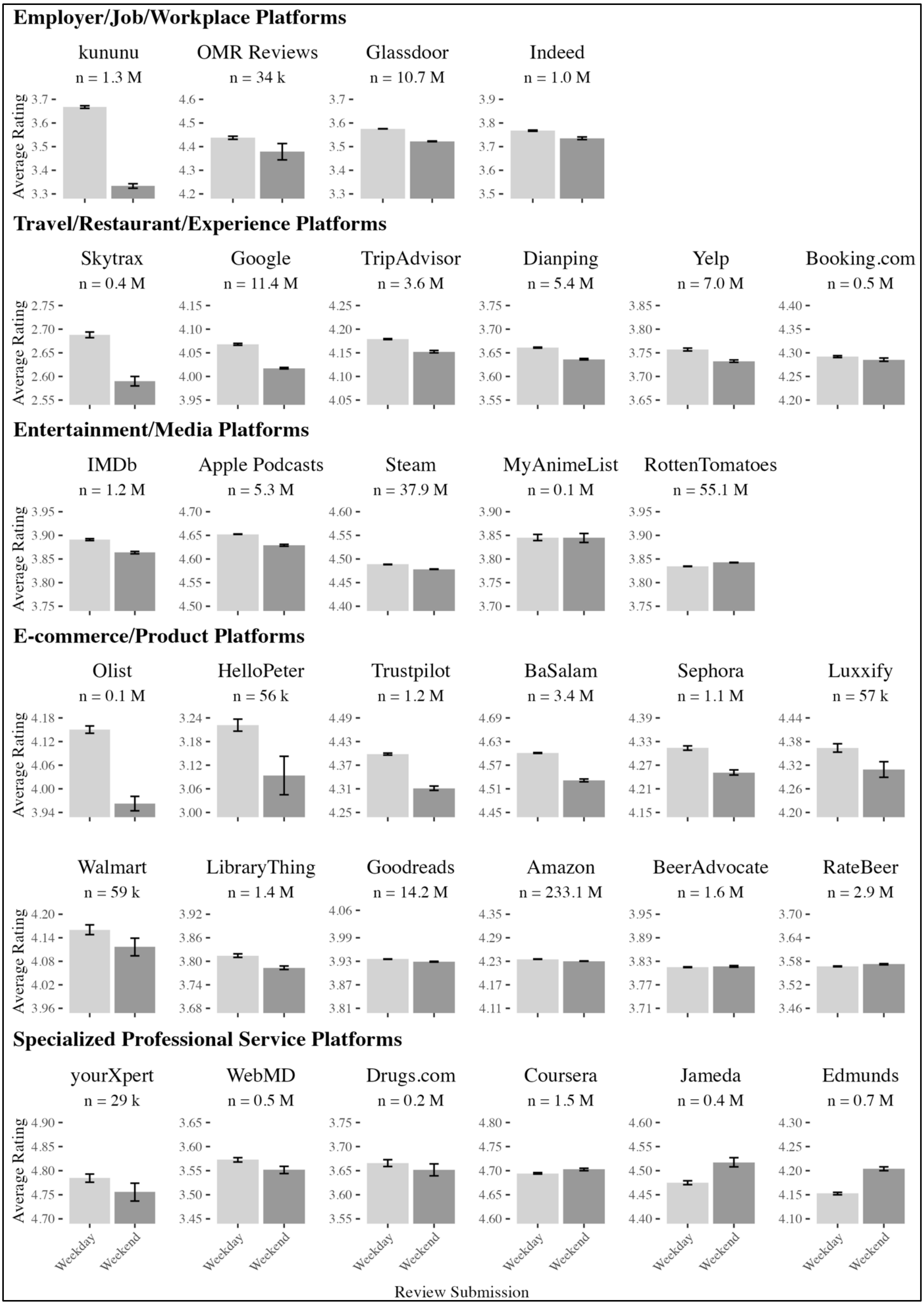
Abstract

This paper finds that online reviews submitted during the weekend tend to have lower rating scores than reviews submitted during the week. Analyzing 400 million reviews across 33 e-commerce, hospitality, entertainment, and employer platforms, the authors find that weekend reviews have a 3% lower relative share of 5-star ratings and a 6% higher relative share of 1-, 2-, or 3-star ratings compared to weekday reviews. The pattern emerges even when controlling for quality of reviewed items. This weekend effect is surprising given that studies usually report higher happiness levels and a better mood on weekends. The authors discuss several explanations related to *where* the review is submitted (platform characteristics), *what* the review is about (listing characteristics), and *who* submits the review (reviewer characteristics). They present evidence that temporal self-selection of reviewers is a dominant driver of the weekend effect. During the weekend, a different set of users—those more prone to write negative reviews—is more likely to select to leave a review. These findings complement extant research on review self-selection by adding a temporal layer to the self-selection processes inherent in online reviews. This paper also highlights managerial implications by demonstrating that solicitations sent during the weekend (versus weekday solicitation) lead to collecting more negative reviews.

Keywords: online reviews, user-generated content, contextual influences, temporal self-selection

Differences between the week and the weekend are widely referred to as "weekend effects" and are well-researched in many disciplines such as healthcare (Bell and Redelmeier 2001), finance (Cross 1973), environmental studies (Cleveland et al. 1974), meteorology (Cerveny and Balling 1998), and psychology (Helliwell and Wang 2015). The mechanisms behind these weekend effects vary depending on the context. In this paper, we uncover a weekend effect in online review ratings that is contrary to the expectation one might have given a generally better mood and higher happiness during the weekend (Stone, Schneider, and Harter 2012; Tsai 2019). We find that online reviews submitted on the weekend consistently carry lower ratings. The robustness of this effect is demonstrated using datasets across 33 major platforms (including Amazon, Glassdoor, Yelp, and IMDb) and almost 400 million reviews, covering more than 20 million reviewed products, movies, services, or employers, from more than 60 million users. The datasets feature a wide range of product and e-commerce, service and leisure, and workplace-related review platforms (see Figure 1).

To establish the robustness of the weekend effect, we first show across our extensive set of online platforms that reviews written on the weekend are consistently worse compared to reviews written during the week. Specifically, we find this to be the case in 26 platforms (79% of all our datasets). We demonstrate the robustness of the effect across different model specifications, including listing- and reviewer-level fixed effects, and by varying the minimum number of reviews required for both reviewers and listings. To better understand the "weekend effect" in online reviews, we tested a large set of potential drivers of this phenomenon. We categorize the potential drivers as related to the platform, the listing, and the reviewer. Regarding platform-specific characteristics, we find that the platform category accounts for most of the variation in the weekend effect, with platforms collecting reviews related to the employer, job, or workplace showing the biggest weekend effect.



Note: “n” denotes the number of online review ratings in this dataset. Whiskers illustrate the 95% CI. For visual comparability, the y-axis range is fixed within each platform category, and axes do not begin at 0. Within each category, platforms are ordered in decreasing size of the weekend effect. Platforms with rating scales other than 1 to 5 stars have been rescaled to a 1 to 5 range.

Figure 1: Average Online Review Ratings Submitted during Weekdays versus Weekends

Regarding listing-related drivers, we find that neither systematic differences between listings (e.g., a product, business, restaurant, hotel, software, movie, or employer) reviewed during the week versus the weekend, nor fluctuations in quality potentially caused by greater crowdedness on weekends in the hospitality sector, can fully explain the effect. In terms of reviewer-related drivers, we find evidence for both within-reviewer and between reviewer differences. However, we find that across most platforms, between-reviewer differences, which we term temporal self-selection, are larger and more consistent than within-reviewer differences, although exceptions exist. Specifically, we identify distinct user segments, observing that those who write reviews on weekends tend to submit lower average ratings compared to those who review exclusively during the week. We find traces in the review texts of these two user segments that are systematically different, revealing potential explanations for the differences in these two groups: Weekend reviewers consistently use fewer words reflecting social processes, i.e., mentions of friends, family, and humans in general. We do not find these textual differences for reviewers who review both during the week and on the weekend. This paints a picture of weekend reviewers being less socially connected. This finding is complemented by additional evidence showing that weekend reviewers have fewer friends – another sign of lower social integration (Falci and McNeely 2009; Ueno 2005). Together, these findings suggest that the weekend effect is less explained by *where* the review is submitted or *what* is being reviewed but rather *who* submits the review, where those opting to write reviews only on the weekend tend to write more negative reviews and show signs of lower social connectedness.

Finally, we demonstrate the practical relevance of the weekend effect for online reviews and show how the effect is meaningful for businesses and platforms despite being small. Our findings imply that the same listing could receive different online review ratings, regardless of the underlying quality, depending on whether the review is composed by a weekend or weekday reviewer, and we find evidence that companies can influence this composition via review solicitation timing. We use various approaches to demonstrate the managerial relevance of the weekend effect of online reviews. First, we highlight the heightened vulnerability of listings with few reviews. Second, we show how the timing of review solicitations can impact the valence of collected online reviews. For businesses, in order to reduce the number of negative reviews written on the weekend, our findings thus suggest to strategically solicit reviews exclusively on weekdays. We test this strategy across five studies on online review platforms for which we know or can approximate when the review was solicited. Two of those are akin to an A/B test in which we randomly solicited reviews during weekdays versus the weekend (one is a field study). Our findings demonstrate that solicited reviews show a weekend effect and support the strategic solicitation of reviews on weekdays to reduce the negative weekend effect.

Our study contributes to the broad literature on weekend effects by introducing a weekend effect in online reviews to marketing research. Further, this work augments the literature on online reviews and particularly self-selection in online reviews by establishing a temporal dimension to self-selection processes based on the day of the week. Moreover, by examining how contextual factors influence audience selection for sharing experiences and the communication of satisfaction, this research highlights the importance of situational factors, particularly the timing of review creation, in shaping electronic word of mouth.

The remainder of the paper is organized as follows. We begin with an overview of relevant literature. Next, we assemble robust evidence for a weekend effect from almost half a billion online reviews across 33 datasets worldwide. Then we explore potential drivers of the weekend effect and identify temporal self-selection as the most empirically supported explanation. We thus investigate the underlying causes of temporal self-selection further and find systematic differences between weekend and weekday reviewers, particularly in their social markers and connections. Finally, we offer managerial implications, discuss the findings, and conclude with suggestions for further research.

Related Literature

Our research is related to three different research streams: user-generated content (UGC) and how it varies across time, self-selection of online reviewers, and contextual influences.

UGC and Temporal Variation

Variations in UGC across time have been analyzed in the context of social media platforms (e.g., Tweets, Facebook postings), blog posts, and music streaming. Given the day of the week, not only do users engage differently (Zor, Kim, and Monga 2022), they also produce other content: Tweets show higher levels of positive affect (Golder and Macy 2011) as well as higher levels of happiness (Dodds et al. 2011) during the weekend compared to weekdays, with some evidence for a small "Blue Monday" (sadness) and a "Thank God It's Friday" (happiness) effect (Stone, Schneider, and Harter 2012). Similar patterns are found for Facebook postings (Kramer 2010; Wang et al. 2014) and blog posts (Mihalcea and Liu 2006). According to Ryan, Bernstein, and Brown (2010), higher happiness on weekends is related to non-work experiences. While findings of past research in an offline (Egloff et al. 1995) and online social media context suggest that, on average, individuals are happier and in a better mood on the weekend, this good mood seems not to spill over to online review ratings.

However, it is essential to account for self-selection when transferring this observation of mood to other contexts such as online review platforms, where underlying motivations to contribute might vary. Whereas both social media and online review platforms tend to not be representative of the general population (Anderson and Simester 2014; Mellon and Prosser 2017), they differ regarding some underlying motivations to create content and engage in either of the two types of UGC (social media postings and online reviews). A literature review on the various underlying motivations (see Table WA1) reveals that while social media content creation and online reviews share some motivations, such as impression management (Berger 2014), other motivations differ significantly between the two. Social media postings are often motivated by self-expression, connection with others, and socialization (Kaplan and Haenlein 2010), whereas online reviews are often related to providing feedback and helping users regulate their emotions through venting (Hennig-Thurau et al. 2004; Hennig-Thurau, Walsh, and Walsh 2003). Given these differences and the subsequent self-selection of users on social media and online review platforms, it is not apparent that the positive weekend effect regarding content on social media platforms translates to reviews written on online review platforms. We are the first to extend the findings of weekend effects in UGC from social media postings to online reviews and thus augment the literature of context and particularly weekend effects in UGC.

Reviewer Self-Selection and Characteristics

Self-selection of reviewers has been shown to affect online reviews (Hu, Pavlou, and Zhang 2017). Past literature identifies different forms of self-selection that affect online ratings such as purchase self-selection (Hu, Pavlou, and Zhang 2017; Kramer 2007), intertemporal self-selection (Li and Hitt 2008; Moe and Schweidel 2012), and polarity self-selection (Hu, Pavlou, and Zhang 2017). Findings regarding intertemporal self-selection and its effect on consumer ratings are particularly relevant to the current research. Intertemporal self-selection refers to consumers reviewing at different times throughout the product lifecycle. For example, Li and Hitt (2008) find differences between early and late reviewers in the product lifecycle, with early reviewers writing more extreme and positive reviews due to self-selection of the type of consumer (early vs. late adopters). Relatedly, there is a debate in political research about how the day of the week affects election polls (Lau 1994) and voting outcomes (Bradfield and Johnson 2017; Sanders and Jenkins 2016), as a different group of people might select to participate in a poll or vote on a weekday versus a weekend, leading to differences in political forecasts and outcomes. Given previous findings that time can impact self-selection and subsequent behaviors, the choice to write reviews and the review content might also change as a function of the day of the week.

Apart from temporal selection of reviewers, past research demonstrates that reviewer characteristics can be associated with differences in online ratings. Moe and Schweidel (2012) show that more active reviewers write more negative and more differentiated reviews. In contrast, less frequent reviewers tend to follow the opinions of previous reviewers. Reviewer expertise has also been associated with harsher evaluations in both online consumer settings (Bondi, Rossi, and Stevens 2024) and offline peer review contexts (Gallo, Sullivan, and Glisson 2016). Personality traits matter as well, as Han (2021) demonstrates, and even interpersonal closeness to an intended audience can influence review valence (Barasch and Berger 2014; Chen 2017; Dubois, Bonezzi, and De Angelis 2016) .

We extend prior literature on intertemporal self-selection and rating differences among reviewer groups by identifying a temporal layer of self-selection related to the weekend that we term “temporal self-selection.”

Contextual Influences

Past research shows that human decision-making can be susceptible to influences from externalities that seem far from obvious and often affect decisions without the person being aware of this influence. This was shown even in critical contexts with highly consequential decisions such as interviewer decisions about medical-student candidates (Redelmeier and Baxter 2009), rulings of judges (Danziger, Levav, and Avnaim-Pesso 2011; Redelmeier and Baxter 2009), or earning calls (Chen, Demers, and Lev 2018), but it is also relevant to consumer activities such as shopping (Ahlbom et al. 2023). Hence one could assume that subtle contextual influences might explain differences between review ratings given on the weekend versus weekdays. Some evidence that contextual influences can affect reviews has been presented by researchers such as Gao et al. (2018), who showed that consumers from countries with high power distance tend to give low ratings to hotels because, without noticing it, they feel superior to the hotels; and Brandes and Dover (2022) showed that bad weather affects review writers and reduces online rating scores. In accord with these findings, a potential contextual influence on online reviews could be the difference between the week and the weekend.

If this is true, the question arises as to what is different between the weekdays and the weekend? Here researchers suggest that on a weekend people are, in general, in a positive emotional state (e.g., Helliwell and Wang 2015; Stone, Schneider, and Harter 2012). Additionally, research on other domains of user-generated content offers ample evidence that an elevated mood on the weekend can lead to more positive information shared during this time (Dodds et al. 2011; Golder and Macy 2011). Following these findings, one could infer that reviews submitted during the weekend are more positive. We conducted an exploratory survey with managers and employees of online review platforms and confirmed that indeed their expectation would also be that online reviews submitted during the weekend are more positive (see Web Appendix B).

However, past literature also finds evidence for what is termed weekend or Sunday neurosis (Maennig, Steenbeck, and Wilhelm 2014), referring to lower levels of reported subjective well-being (Akay and Martinsson 2009) and life satisfaction on a Sunday (Kavetsos, Dimitriadou, and Dolan 2014). Moreover, it is for this reason that the weekend is the most frequent time for suicide attempts (Klemesrud 1976). The observation of Sunday neurosis dates back to Ferenczi (1919) and Frankl (1959), and terms like weekend blues, weekend gloominess, Sunday malaise, or weekend loneliness have long been common. Thus, past findings on contextual influences do not give a clear picture of how reviews might be affected during the week versus the weekend.

In what follows, we first present evidence for a weekend effect across 33 datasets and demonstrate robustness of the effect across multiple model specifications controlling for listing or reviewer characteristics. Additionally, we show that a similar effect appears on public holidays. We next present a comprehensive set of potential explanations for the weekend effect and test their ability to explain the observations. We then build on our results and discuss their managerial implications across five additional studies, including a field experiment.

Evidence for a Weekend Effect in Online Reviews

We use 33 different online review datasets to incorporate various types of targets being reviewed. The datasets can be grouped into five different categories: product and e-commerce reviews (e.g., Amazon, Sephora); travel, restaurant, and experience reviews (e.g., Yelp, Google, TripAdvisor) with the predominant category being restaurants and hotels; employer, job, and workplace-related reviews (e.g., Glassdoor or smaller, less known software review sites); entertainment and media-related reviews (e.g., IMDb, Rotten Tomatoes); and finally reviews related to specialized professional services (e.g., Coursera or lawyer review sites). Table 1 gives a comprehensive overview and descriptives of our datasets. Table WC5 provides an overview of our data sources used. Across most datasets, we code Saturdays and Sundays as being the weekend, which is in line with what a vast majority of countries consider as “weekend”. Only for BaSalam, an e-commerce review platform in Iran, did we code Friday (and Saturday) as the weekend, because in Islam, Friday (“Yawm al-Jumu'ah”) is the holy day, similar to Sunday in Christianity or Saturday (“Shabbat”) in Judaism.

Model-Free Evidence

Concentrating on our focal variable, the review valence (i.e., the star rating), we find consistent evidence for a weekend effect in online reviews across our comprehensive datasets spanning 33 online review platforms and nearly 400 million reviews (see Figure 1). First, our results show a significant ($p < .001$) overall main effect, confirming that reviews written on the weekend are significantly more negative, on average by .04 stars. Focusing on each individual platform, we find a significant negative weekend effect in 26 platforms (79%), while 2 platforms (6%) show no significant difference, and 5 platforms (15%) show a small, reversed weekend effect (see Table 1). Regarding review volume, on 26 of 33 platforms, less reviews are submitted on a typical weekend day compared to a typical weekday (see Table 1).

To incorporate the full distribution of online review ratings submitted on weekdays and weekend days, we follow standard industry practices using the net promoter score (NPS) and classify ratings as either detracting or promoting. We find that relative to the weekday distribution, on weekends the percentage of reviews classified as "promoting" (i.e., 5-star ratings) is on average 3.0% lower (min = -19.6%; max = 3.7%), while those considered "detracting" (i.e., 1-, 2-, 3-star ratings) is on average 5.7% higher (min = -10.2%; max = 34.6%). This suggests that the weekend effect is driven by fewer 5-star reviews and more 1-, 2-, and 3-star reviews submitted on weekends.

In addition to the consistent weekend effect across platforms as shown in Figure 1, we see when zooming in on online review ratings submitted on different days of the week that across weekdays, no clear and consistent pattern emerges across all platforms (see Figure WC2). In this paper we focus on differences between weekdays and weekends, but we discuss later how future research could extend our results to different days of the week.

Platform	Platform category	Weekend effect	Vol. change weekend	Public holiday effect	Distribution (Week/Weekend)					Rel. diff. in promoter share (weekend; in %)	Rel. diff. in detractor share (weekend; in %)	Robustness		
					% 5-stars	% 4-stars	% 3-stars	% 2-stars	% 1-star			5-core subset	within-reviewer	within-listing
kununu	Employer/Job/Workplace	-.33***	-74%	-.22***	36.7/29.5	27.8/22.8	12.8/14.8	14.1/19.7	8.6/13.3	-19.6	34.6	-.17***	-.12***	-.23***
Olist	E-commerce/Product	-.19***	-20%	-.08*	59.1/55.2	19.7/18.4	8.3/8.3	3.0/3.6	9.9/14.5	-6.6	24.5	-.18***	/	-.16***
HelloPeter	E-commerce/Product	-.13***	-75%	-.26***	43.1/41.6	9.9/7.4	2.8/3.7	14.7/13.5	29.6/33.8	-3.5	8.3	-.33*	-.02	-.18***
Skytrax	Travel/Restaurant/Experience	-.10***	-21%	/	22.8/21.3	16.5/15.6	8.8/8.2	11.3/11.0	40.6/43.8	-6.6	3.8	-.11***	-.06*	.01
Trustpilot	E-commerce/Product	-.09***	-41%	/	76.4/73.4	8.0/8.4	3.5/4.3	3.2/3.8	8.9/10.1	-3.9	16.7	-.09***	-.16*	-.18
BaSalam	E-commerce/Product	-.07***	-41%	-.08***	78.6/75.8	11.4/12.2	5.0/5.7	1.7/2.1	3.4/4.3	-3.6	19.8	-.06***	-.06***	-.06***
Sephora	E-commerce/Product	-.06***	-22%	/	64.2/62.8	18.4/17.7	7.4/7.7	4.7/5.4	5.3/5.4	-2.2	6.3	-.09***	-.01	-.06***
OMR Reviews	Employer/Job/Workplace	-.06***	-90%	/	60.7/55.1	31.2/35.5	5.9/6.9	1.4/1.6	0.8/0.8	-9.2	14.8	-.15***	-.01	-.06
Luxxify	E-commerce/Product	-.06***	-19%	/	67.6/66.6	16.4/15.6	6.2/6.6	4.2/4.3	5.6/6.8	-1.5	10.6	-.07**	-.01	-.03
Glassdoor	Employer/Job/Workplace	-.05***	-42%	/	27.8/26.0	30.1/30.3	23.0/23.5	10.1/10.5	9.0/9.8	-6.5	4.0	-.06***	/	-.08***
Google	Travel/Restaurant/Experience	-.05***	-1%	-.03***	51.5/47.6	22.5/24.9	12.6/14.2	8.0/8.2	5.4/5.1	-7.6	5.8	-.02***	-.01***	-.02***
Walmart	E-commerce/Product	-.04***	-20%	-.08*	63.7/62.2	15.3/15.8	5.6/5.7	4.0/4.1	11.3/12.2	-2.4	5.3	-.05***	.01	-.04
Indeed	Employer/Job/Workplace	-.03***	-41%	/	32.5/31.6	31.7/31.6	22.2/22.3	7.3/7.5	6.3/6.9	-2.8	2.5	-.03***	/	-.02
LibraryThing	E-commerce/Product	-.03***	+1%	/	31.0/29.6	40.1/40.3	20.1/20.8	6.3/6.6	2.5/2.7	-4.5	4.2	-.03***	-.00	-.02***
yourXpert	Spec. Professional/Service	-.03**	-36%	-.10*	89.8/88.6	5.8/6.2	1.4/1.8	1.0/1.0	2.1/2.5	-1.3	17.8	/	/	/
IMDb	Entertainment/Media	-.03***	+38%	/	29.9/27.5	40.7/42.1	21.8/23.3	4.1/4.1	3.4/3.1	-8.0	4.1	-.03***	-.01	-.02***
TripAdvisor	Travel/Restaurant/Experience	-.03***	-21%	-.02***	40.7/38.8	33.0/33.6	13.8/14.7	6.6/6.9	5.9/6.0	-4.7	4.9	-.00	-.02**	-.04*
Dianping	Travel/Restaurant/Experience	-.03***	-8%	-.02***	14.2/14.0	47.0/46.1	32.1/32.2	4.2/4.6	2.5/3.0	-1.4	2.6	.03***	-.03***	-.01***
Yelp	Travel/Restaurant/Experience	-.03***	+17%	-.04***	46.4/45.9	20.9/20.5	9.9/10.0	7.6/8.2	15.2/15.4	-1.1	2.8	-.02***	-.05***	-.02***
Apple Podcasts	Entertainment/Media	-.02***	-34%	/	87.4/86.7	2.9/3.1	2.3/2.3	2.0/2.1	5.2/5.8	-0.8	7.4	-.02***	-.01**	-.02***
WebMD	Spec. Professional/Service	-.02***	-18%	-.01	31.8/31.4	26.1/26.0	18.0/17.9	15.8/16.0	8.3/8.7	-1.3	1.2	-.02***	/	-.03
Drugs.com	Spec. Professional/Service	-.01*	-17%	-.06***	48.7/48.7	17.6/17.3	8.9/8.8	7.2/6.9	17.6/18.3	-0.0	0.9	-.02*	/	-.06*
Steam	Entertainment/Media	-.01***	+16%	/	87.2/87.0				12.8/13.0	-0.2	1.6	-.00***	/	-.00*
Goodreads	E-commerce/Product	-.01***	-6%	/	35.6/35.3	34.7/34.7	20.0/20.2	6.9/7.0	2.7/2.8	-0.8	1.4	-.01***	-.01*	-.00
Booking.com	Travel/Restaurant/Experience	-.01**	-10%	/	48.2/48.2	38.9/38.5	9.9/10.2	3.0/3.1	0.0/0.0	-0.0	3.1	-.01**	/	-.02
Amazon	E-commerce/Product	-.01***	-15%	/	63.8/63.7	16.1/16.1	7.7/7.6	4.7/4.7	7.7/7.9	-.0.2	0.5	-.01***	-.01***	-.01***
My Anime list	Entertainment/Media	-.00	+13%	/	38.8/38.7	32.8/32.7	15.6/15.8	8.5/8.3	4.4/4.4	-0.3	0.0	-.00	-.02	.01
BeerAdvocate	E-commerce/Product	.00	+10%	/	26.3/26.0	55.6/56.1	14.2/14.1	3.3/3.2	0.7/0.7	-1.1	-1.1	.00	.00	.00
RateBeer	E-commerce/Product	.01***	+18%	/	5.7/5.4	60.3/60.8	24.7/24.8	7.5/7.4	1.8/1.6	-5.3	-0.6	.03***	.01	-.04***
RottenTomatoes	Entertainment/Media	.01***	-1%	/	38.0/38.3	29.1/29.3	18.0/17.7	8.0/7.8	6.9/6.9	0.8	-1.5	.01***	.01*	-.01
Coursera	Spec. Professional/Service	.01***	-5%	/	78.7/79.1	15.6/15.5	3.3/3.3	1.1/1.0	1.2/1.2	0.5	-1.8	.01***	.01**	.01
Jameda	Spec. Professional/Service	.04***	-58%	.04*	81.2/82.9	4.5/3.8	3.2/3.1	5.5/5.4	5.6/4.9	2.1	-6.3	.04***	/	.00
Edmunds	Spec. Professional/Service	.05***	-8%	.01	48.3/50.1	34.2/34.2	10.0/9.2	5.0/4.4	2.6/2.2	3.7	-10.2	.05***	.00	.06***

Note: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$. *Weekend Effect* = average weekend rating − average weekday rating. *Public Holiday Effect* = average public holiday rating − average rating on non-holiday weekdays. Public holiday inference was only possible when we were sure the platform only operates in one country or we had information on the location of reviewers. We compared the change in review volume between an average weekend day and an average weekday. All rating scales were normalized to a 1–5 scale. Following industry standards, we define promoters as 5-star reviews and detractors as 1-, 2-, or 3-star reviews.

Table 1: Model-Free Evidence for the Weekend Effect on Different Online Review Platforms

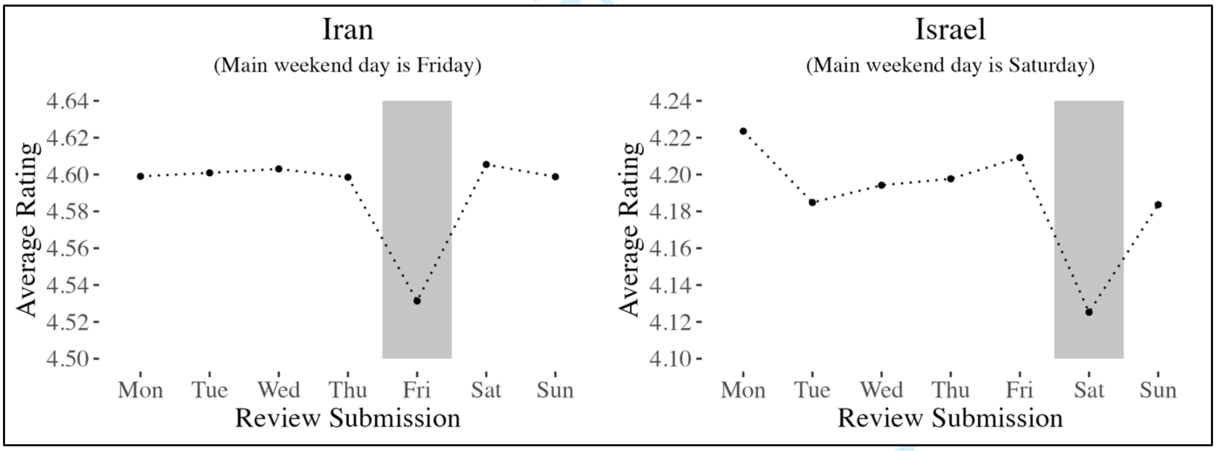
Robustness of the Weekend Effect

Different subsets. We demonstrate the robustness of the weekend effect in different subsets, as can be seen when looking at within-listing differences in Table 1 (i.e., listings that received reviews during both the week and weekend). The evidence disproves the possibility that during the weekend worse products, businesses, or employers are being reviewed, as the weekend effect tends to persist even for the same listing.

The results in Table 1 also show that the weekend effect is robust to different specifications such as considering only reviewers who have written at least five reviews and reviewed listings that have accumulated at least five reviews ("5-core subset"). To further assess the robustness across different cut-offs, we test the weekend effect within subsets of reviewers or listings with a minimum number of reviews (see Figure WC3 and WC4 in Web Appendix C). The following patterns appear: On some platforms, subsets of reviewers with greater experience (i.e., having submitted more reviews), are associated with smaller weekend effects (see e.g., kununu, BaSalam, Google, Dianping, or Yelp), whereas on other platforms, the weekend effect is larger among more experienced reviewers (see, e.g., Sephora and Amazon) (see Figure WC3). In subsets of listings with a high number of reviews, we again find no consistent pattern in how the weekend effect changes (see Figure WC4). Overall, the key insight from these analyses is that the weekend effect is robust, even in datasets comprising experienced reviewers or review targets with a substantial number of existing reviews.

Across geographies. Furthermore, we find that the weekend effect is consistent across geographic locations. For instance, the restaurant review platforms Yelp (USA) and Dianping (China) both exhibit a significant weekend effect, with similar patterns in review ratings across the week (see Figure WC2), despite operating on opposite sides of the globe. This pattern holds for employer review platforms such as Glassdoor and Indeed (mainly USA) versus kununu (Germany), as well as for e-commerce marketplaces like Amazon (primarily northern hemisphere, USA) compared to Olist (Brazil, southern hemisphere), Trustpilot (Denmark), or Hellopeter (South Africa). And within our dataset of worldwide Google reviews (the only dataset with reviews from all around the world), we find that the weekend effect is significant across the 10 biggest countries (w.r.t. review volume).

Most reviews in our dataset probably stem from a location where the weekend is commonly defined as Saturday and Sunday, but there are two notable exceptions: Iran with Friday ("Yawm al-Jumu'ah") and Israel with Saturday ("Shabbat") as the most prominent weekend day. In line with that, in the dataset of the Iranian BaSalam e-commerce marketplace, Friday has the lowest online review rating scores. For Google reviews of businesses in Israel, indeed Saturday is the day where the worst reviews are submitted (see Figure 2).



Notes: Left: 3.4 M online reviews from BaSalam (Iranian e-commerce platform). Right: .1 M Google reviews subsetted for businesses in Israel.

Figure 2: Average Online Review Ratings Across Countries with Different Weekends

Regression Analysis with Fixed Effects

We confirm our results from Table 1, running regressions for all datasets for which we found a significant weekend effect in the model-free evidence (see Table 1, column "weekend effect"). Our dependent variable is the review valence (i.e., the star rating) submitted by reviewer r, at time t, for the review target i. The latter is the listing being reviewed (i.e., a product, business, restaurant, hotel, software, movie, or employer). The main independent variable of interest is a dummy variable that indicates whether this review was submitted during the weekend (0 = no; 1 = yes). The unit of analysis is a review. We control for both the review valence and volume at *t-1* of review target *i*, capturing both the average rating and the number of reviews that a user would be exposed to – and potentially influenced by – at time *t* (Lee, Hosanagar, and Tan 2015). Thus, these covariates are time-varying and are therefore separately identified from reviewer and business fixed effects, accounting for time-invariant heterogeneity. Table 2 shows the results without fixed effects, while in Table 3 we add reviewer fixed effect (γ_r) and business fixed effect (δ_i), whenever the data availability permits. The model including reviewer and listing fixed effects is thus specified as follows:

$$Star\ Rating_{rti} = \beta_1 Weekend_{rti} + \beta_2 Average\ Rating_{i,t-1} + \beta_3 Review\ Volume_{i,t-1} + \gamma_r + \delta_i + \varepsilon_{rti}$$

Results in Table 3 indicate a significant negative effect of the weekend dummy, confirming that reviews submitted during weekends tend to have lower ratings. With listing fixed effects added, 24 of 26 platforms that have a weekend effect in the model-free evidence (Table 1) still show a significant weekend effect (see Table WD1). Even after we control for both listing- and reviewer-level fixed effects (when possible), the negative weekend effect remains statistically significant for two thirds of the platforms (17 of 26 platforms; Table 3). For a few platforms the effect becomes insignificant once fixed effects are included, likely due to a focus on reviewers who only wrote reviews during the week and the weekend as we explain later as well as a substantial loss of observations from reviewers who wrote only one review or listings with a single review. Web Appendix D reports the results where fixed effects are gradually added (i.e., first none, then only reviewer fixed effects, then only business fixed effects, then both).

	Dependent Variable: Star Rating$_t$																									
	kununu	Olist	HelloPeter	Skytrax	TrustPilot	BaSalam	Sephora	OMR Reviews	Luxxify	Glassdoor	Google	Walmart	LibraryThing	Indeed	yourXpert	IMDb	TripAdvisor	Dianping	Yelp	Apple Podcasts	WebMD	Drugs.com	Steam	Goodreads	Booking.com	Amazon
Weekend	-.26***	-.19***	-.19**	-.04***	-.02	-.07***	-.04***	-.06	-.03**	-.04***	-.04***	-.06***	-.03***	-.03***	-.07**	-.04***	-.04***	-.02***	-.05***	-.01***	-.02***	-.05**	-.00***	-.00***	-.02**	-.01***
(0=no; 1=yes)	(.00)	(.01)	(.06)	(.01)	(.03)	(.01)	(.00)	(.05)	(.01)	(.00)	(.00)	(.01)	(.00)	(.01)	(.02)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.02)	(.00)	(.00)	(.00)	(.00)
Avg. rating$_{t-1}$	.63***	.19***	1.09***	.42***	.96***	.24***	.87***	.56***	.58***	.84***	.42***	.43***	.41***	1.01***	/	.85***	.79***	.65***	.82***	.91***	.72***	.89***	.94***	.62***	.88***	.41***
	(.00)	(.01)	(.06)	(.01)	(.06)	(.00)	(.00)	(.02)	(.02)	(.01)	(.00)	(.01)	(.00)	(.03)		(.01)	(.00)	(.00)	(.00)	(.01)	(.01)	(.02)	(.05)	(.00)	(.01)	(.00)
Rev.volume$_{t-1}$	.01***	-.00	-.04***	-.10***	.04**	-.02***	-.01***	.01*	.01***	.02***	.05***	.04***	.01***	.03***	/	-.00	.02***	.02***	.03***	-.02***	-.01***	-.07***	.00***	.01***	-.01***	.01***
	(.00)	(.01)	(.08)	(.01)	(.01)	(.00)	(.00)	(.01)	(.01)	(.00)	(.00)	(.01)	(.00)	(.01)		(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.00)	(.00)	(.00)	(.00)
Fixed Effects																										
Reviewer	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Listing	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Observations	1.1M	67k	56k	0.4M	1.2M	2.7M	1.1M	32k	56k	10.7M	7.4M	59k	1.0M	1M	29k	1.2M	3.5M	5.4M	6.8M	5.3M	0.5M	0.2M	38M	13.0M	0.5M	17.9M
Adj. R^2	.14	.02	.35	.24	.13	.02	.06	.09	.07	.09	.10	.07	.06	.06	.00	0.20	.12	.10	.19	.18	.07	.12	.14	.10	.13	.05
# reviewers	1.0M	/	49k	0.1M	0.4M	0.9M	0.5M	3k	31k	/	4.1M	43k	65k	/	/	0.2M	1M	0.5M	1.9M	3.1M	/	/	/	0.4M	/	10.1M
# listings	0.2M	32k	68	2k	244	0.7M	2k	13k	1k	36k	1.7M	8k	0.1M	466	/	40k	37k	0.2M	0.2M	0.3M	8k	4k	8k	1.2M	2k	2.3M

Notes: ***$p < .001$, **$p < .01$, *$p < .05$. For Amazon we took a smaller random subset of the entire available data. Standard errors in parentheses. Errors clustered at the listing level.

Table 2: Regressions, no Fixed Effects

	Dependent Variable: Star Rating$_t$																									
	kununu	Olist	HelloPeter	Skytrax	TrustPilot	BaSalam	Sephora	OMR Reviews	Luxxify	Glassdoor	Google	Walmart	LibraryThing	Indeed	yourXpert	IMDb	TripAdvisor	Dianping	Yelp	Apple Podcasts	WebMD	Drugs.com	Steam	Goodreads	Booking.com	Amazon
Weekend	-.06***	-.18***	-.02	-.02*	-.04*	-.03***	-.00	.04	-.01	-.04***	-.00*	-.04	.00	-.03***	-.07**	-.00	-.04***	-.01***	-.03***	-.01***	-.02***	-.03*	-.00***	-.00	-.02**	-.01***
(0=no; 1=yes)	(.01)	(.01)	(.05)	(.00)	(.02)	(.00)	(.00)	(.10)	(.02)	(.00)	(.00)	(.04)	(.00)	(.01)	(.02)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.02)	(.00)	(.00)	(.00)	(.00)
Avg. rating$_{t-1}$	-.00	-.61***	.79***	.43***	1.26***	-.46***	.31***	-.37***	-.19***	.53***	-.34***	-.51***	-.41***	-.75***	/	-.05***	.11***	-.10***	-.04***	.27***	-.07***	.18***	1.01***	-.18***	.03	-.35***
	(.00)	(.02)	(.09)	(.02)	(.06)	(.00)	(.02)	(.06)	(.04)	(.02)	(.00)	(.05)	(.00)	(.45)		(.01)	(.01)	(.00)	(.00)	(.02)	(.02)	(.03)	(.06)	(.00)	(.00)	(.00)
Rev.volume$_{t-1}$	-.01	-.09***	-.13***	-.15***	-.09	-.06***	-.05***	-.05	-.13***	.08***	-.02***	.03	-.11***	-.03***	/	-.13***	.02***	-.03***	-.06***	-.07***	-.07***	-.43***	.01***	.00	-.00	-.05***
	(.01)	(.01)	(.03)	(.01)	(.06)	(.00)	(.00)	(.03)	(.01)	(.00)	(.00)	(.03)	(.00)	(.02)		(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.02)	(.00)	(.00)	(.00)	(.00)
Fixed Effects																										
Reviewer	✓	x	✓	✓	✓	✓	✓	✓	✓	x	✓	✓	✓	x	x	✓	✓	✓	✓	✓	x	x	x	✓	x	✓
Listing	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	0.3M	61k	12k	0.1M	9k	2.2M	0.8M	16k	30k	10.7M	3.8M	12k	0.9M	1M	29k	1M	2.9M	5M	5.7M	2.8M	0.5M	0.2M	38M	12.7M	0.5M	10.4M
Adj. R^2	.54	.11	.68	.51	.32	.35	.41	.29	.16	0.11	.45	.21	.33	.06	.00	.45	.18	.31	.37	.42	.09	.15	.15	.36	.14	.31
# reviewers	0.1M	/	5k	16k	2k	0.4M	0.2M	3k	6k	/	0.9M	3k	42k	/	/	72k	0.4M	0.4M	0.8M	0.8M	/	/	/	0.3M	/	3.1M
# listings	49k	8k	64	1k	194	0.3M	2k	1k	1k	25k	1.0M	3k	88k	466	/	18k	27k	0.1M	0.2M	0.1M	5k	2k	8k	0.5M	2k	1.4M

Notes: ***$p < .001$, **$p < .01$, *$p < .05$. For Amazon we took a smaller random subset of the entire available data. Standard errors in parentheses. Errors clustered at the listing level.

Table 3: Regressions, with Fixed Effects

The Case of Public Holidays: A public holiday effect?

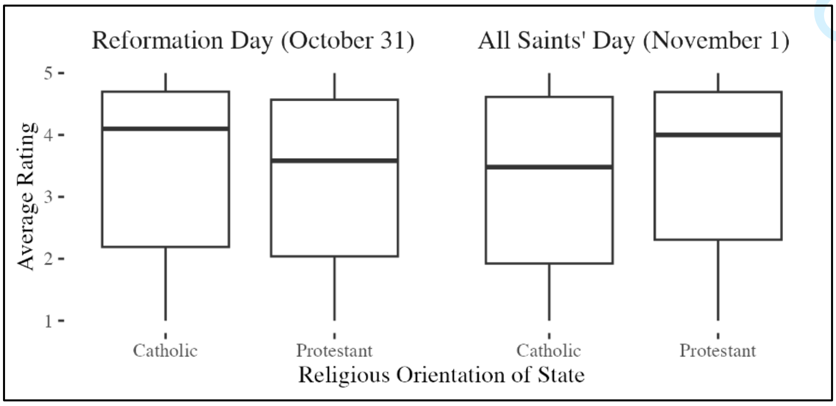
The purpose of this analysis is to examine whether the weekend effect extends beyond the periodicity of a seven-day cycle and manifests on public holidays, which share characteristics with weekends, such as work-free status and altered daily routines. Indeed, in finance, not only a weekend effect but also a holiday effect has been found (Thaler 1987). Similarly, in medicine, the weekend effect holds on public holidays (Sharp, Choi, and Hayward 2013). Given these results, we investigate online reviews and their rating on public holidays (e.g., Labor Day, Christmas) for robustness and conceptual replication of the weekend effect. We further leverage a setting similar to a natural experiment across a space and time dimension (i.e., a certain location where a given day is a public holiday vs. another location where it is not).

To do so we acquired a dataset of public holidays for countries in our dataset with the *nager.date API* and merged this information with our datasets where users' and businesses' locations can be reliably determined or inferred (14 platforms, see Table WC1). We calculate a "Public holiday effect", which we define as the average rating on a public holiday minus the average rating on non-holiday weekdays (see Table 1). We find that online review ratings submitted on public holidays in the respective country are similar to online review ratings submitted during weekends. Overall, we find a public holiday effect for 11 of the 14 (79%) platforms. On average, the public holiday effect is similar in size to the weekend effect in online review ratings. It is important to note that this analysis is constrained by local variations in the definition of public holidays and by individual differences in the relevance attributed to specific holidays.

To further test the difference in reviews written on public holidays, we use the context of public holidays in Germany, which differ between states. Historically, some federal states in Germany such as Bavaria were more Catholic, whereas other federal states such as

Schleswig-Holstein were more Protestant. These influences and the federal system have led to differences in public holidays across the federal states that persist today. For example, All Saints' Day ("Allerheiligen") on November 1st is a public holiday only in Catholic federal states, whereas Reformation Day ("Reformationstag") on October 31st is a public holiday only in Protestant federal states. This holds for everyone working in a federal state, independent of one's personal religion. This setting thus allows us to compare reviews written in states that were subject to a public holiday versus not. We expect to find worse reviews in those federal states where the respective day is a work-free public holiday compared to the control group of states where the respective day is a normal working day.

To test this, we use the dataset of employer reviews in Germany, which for some reviews includes a variable about the federal state of the reviewed business. Figure 3 supports our hypothesis. The average rating on Reformation Day, which is a work-free public holiday only in Protestant federal states, is significantly worse in Protestant federal states (M = 3.28) compared to Catholic federal states (M = 3.52, t(668) = 2.98, $p < .01$). Vice versa, on All Saints' Day, which is a work-free public holiday only in Catholic federal states, review ratings are significantly better in Protestant states (M = 3.50) than in Catholic states (M = 3.26, t(1028) = -3.09, $p < .01$).



Note: Reformation Day is a public holiday in 9 Protestant states in Germany. All Saints' Day is a public holiday in 5 Catholic states in Germany. N = 1,630 (1,397) employer reviews written on Reformation Day (All Saints' Day) for which the state of the reviewed business (and thus the assumed reviewer location) is known.

Figure 3: Average Online Review Rating across German States with Different Public Holidays

Explaining the Weekend Effect

So far, we have established that the weekend effect exists and is robust for most online review platforms across a diverse and comprehensive set of categories (see Table 1). We further showed its robustness in different subsets (i.e., reviewers or listings with at least a certain number of reviews, see Web Appendix D) and tested different model specifications, such as controlling for listing and reviewer characteristics (see Tables 2 and 3).

Next, we discuss and examine a comprehensive set of potential explanations for the weekend effect, where some explanations can only apply to some of the datasets (e.g., how crowded the place is can only matter for services). We categorize these explanations as platform-, listing-, and reviewer-related. Additionally, we distinguish between explanations that operate within a single platform, listing, or reviewer and those that arise between different platforms, listings, or reviewers. Within-explanations pertain to variations specific to a given platform, listing, or individual reviewer over time, while between-explanations address differences observed between distinct platforms, listings, or groups of reviewers, such as variations in products or reviewer demographics. Table 4 summarizes these explanations and their supporting empirical evidence, discussed in detail below. The explanation for which we find the most consistent evidence and that may apply universally across platforms from all categories is a reviewer-related explanation, namely temporal self-selection referring to between reviewer differences. We also observe some, though less consistent, evidence for within reviewer differences as well as an amplification of the weekend effect for some platforms (e.g., employer reviews) and via restaurant crowdedness.

Potential explanation	Reasoning	Evidence for or against
Platform-specific explanations		
Within platform:		
Online review manipulation	Assuming that fake reviews are rather positive, it could be that fake reviewers are less active during the weekend.	Fake reviews are not necessarily only positive. And we find that the weekend effect persists in verified reviews. Also, in a cross-platform analysis, we find no significant relation between platforms labeling verified reviews and the weekend effect.
Between platforms:		
Platform features	Difference in platform features (e.g., rating scale) might explain why the weekend effect is stronger on some platforms compared to others.	Cross-platform analysis shows that it is mainly the category of the platform that relates significantly to the existence and size of the weekend effect.
Listing-specific explanations		
Within listing:		
Crowdedness leading to varying quality	It could be that restaurants or other locations are more crowded during the weekend, making the whole experience less pleasant and leading to more negative reviews.	Crowdedness can only be an explanation for platforms in one of our five categories (i.e., the category of travel, restaurants, and experiences). We also show that the weekend effect persists for restaurants that are equally crowded throughout the week. However, for especially crowded restaurants, the weekend effect is slightly bigger.
Between listings:		
Different listings being reviewed	It could be that listings being reviewed during the weekend have systematically worse quality.	We find that the weekend effect persists on most platforms when including listing fixed effects.
Reviewer-specific explanations		
Within reviewer:		
Additional time on weekends	It could be that because users have more time during the weekend to reflect critically, they find more negative aspects of the experience and thus write more negative reviews.	The text of weekend reviews doesn't confirm this explanation. Weekend reviews can be shorter and tend to show less signs of analytical thinking and cognitive processes.
Delaying negative reviews until the weekend	Given that past research finds that negative reviews are usually longer, it could be that users postpone writing their negative review to the weekend, because they know that they will have more time.	We find no significant empirical evidence suggesting that the effect of time passed between an experience and the review submission varies by review timing.
Higher expectations	It could be that users have higher expectations during the weekend. Thus, the same experience during the weekend could be perceived worse than during the week.	This could be true for experiences such as restaurant visits. For employers, products, or other services, it is unlikely that one would have higher expectations during the weekend.
Between reviewers:		
Temporal self-selection	There could be a temporal self-selection of people such that those who decide to review during the weekend are different from those writing reviews on the weekdays.	We find a substantial number of reviewers who only review during the weekend, and these reviewers review worse than those who only review during the week. Additionally, weekend reviewers' texts (vs. weekday reviewers' texts) show fewer social cues and more words related to sadness. Furthermore, weekend reviewers have fewer social connections.

Table 4: Potential Explanations for the Weekend Effect

Platform-Specific Explanations

The weekend effect in online reviews might stem from platform-specific explanations, both "within" a single platform and "between" different platforms. Within-platform explanations could involve aspects specific to a platform that change in the course of a week, such as review manipulation or fake reviewing might. Between-platform explanations pertain to variations across platforms themselves (e.g., different rating scales).

Within platform – Online review manipulation. One could argue that fake reviews or online review manipulations (as covered in Mayzlin, Dover, and Chevalier 2014) are responsible for the weekend effect. On weekends, professional fake reviewers who typically write positive reviews may be less active, potentially leading to lower average ratings and contributing to the observed weekend effect.

We argue that this is unlikely for the following reasons: First, fake reviews are not necessarily positive—they can also be negative, written by competitors (Luca and Zervas 2016). Thus, if fake reviewers are less active during the weekend, we should see a reduction in both very positive and very negative reviews. However, among reviews submitted on a weekend, we observe a lower share of very positive reviews and a higher share of negative reviews (see Table 1). Second, we find that the weekend effect persists on platforms that consciously make efforts to reduce fake reviews or where fake reviews are arguably absent (i.e., yourXpert and Yelp). Third, the weekend effect also holds when restricting the analysis to verified reviews (Amazon) or active reviews (kununu) only (see Web Appendix E).

Altogether, we find no evidence to support a claim that fake reviewing can explain the weekend effect, as the weekend effect persists even in datasets and contexts where fake reviews are minimized and accounted for.

Between platforms – Platform features. To investigate whether specific platform features are associated with the weekend effect, we collected a set of platform characteristics (see Table WC1) and ran a review-level regression with the numeric rating as the dependent variable. The regression includes interactions between each platform characteristic and a weekend indicator to assess which features amplify or attenuate the weekend effect. To create a balanced dataset across platforms, we randomly sampled an equal number of observations from each of the 33 datasets and combined them into a single dataset. All rating scales were linearly rescaled to a common range from 1 to 5. The platform characteristics include: (1) the platform category, (2) the ratio of weekday to weekend review volume, (3) positive imbalance among all existing reviews on the platform (defined as in Schoenmueller, Netzer, and Stahl 2020), (4) type of business model, (5) availability of a reviewer social network feature, (6) presence of reviewer recognition features, (7) availability of a verified review functionality, and (8) ability for businesses to respond to reviews.

We report the full regression in Web Appendix F. In summary, we find a negative main effect of the weekend indicator (-.05; SE = .01; $p < .001$), indicating that reviews written on weekends are, on average, less positive. Among the 33 platforms studied, this negative weekend effect is attenuated when platforms offer a reviewer social network. This may be because, under these conditions, review content resembles other user-generated content, such as typical social media posts (see Web Appendix A), where, as discussed previously, weekends are associated with more positive content submissions.

However, the weekend effect becomes even stronger on platforms where verified reviews are enabled and where responses to reviews are supported, suggesting that features promoting accountability amplify the weekend-related decline in star ratings. Regarding the platform category, the weekend effect is strongest for Employer/Job/Workplace platforms and weakest (or even reversed in a few cases) for platforms focusing on specialized services (e.g., Coursera) or with a pure focus on one product (e.g., Edmunds). We can only speculate why platforms in the employer, job, and workplace category show a more pronounced weekend effect. It is possible that individuals thinking about job-related matters during the weekend may be experiencing significant dissatisfaction at work. For most people, work is typically not a top priority during the weekend unless they are facing serious issues. A heightened focus on work-related issues during leisure time could coincide with a greater likelihood of leaving a review, which is more likely to be negative.

Listing-Specific Explanations

Potential explanations of the weekend effect related to what is being reviewed have two sources. It could be that the same target being reviewed during the week and the weekend changes ("within listing"): An obvious explanation would be crowdedness of businesses during the weekend. The other string of explanations revolves around different targets being reviewed during the week and weekend ("between listings").

Within listing – Quality fluctuations/crowdedness. Businesses oftentimes experience higher traffic on weekends, particularly in settings like restaurants. Crowdedness can lead to slower service, longer queues, and higher stress levels among service employees, resulting in a lower-quality customer experience. As a result, the same business might receive more negative reviews on weekends than on weekdays, simply due to the impact of crowd-induced variations in service quality.

Notably, crowdedness can explain the weekend effect only for platforms in one of our five categories: travel, restaurants, and experiences. Here, it could be that quality fluctuates between weekdays and weekends, but this is unlikely for products and employers, where the perceived underlying quality of what is being reviewed is presumably stable, at least throughout the time frame of a week. Since we demonstrate that the weekend effect persists across four other platform categories—including e-commerce products and employers—where quality should remain consistent at least throughout the week, quality variation between the week and weekend cannot be a universal explanation for the weekend effect.

For a few of our datasets in the travel, restaurant, and experience category, however, crowdedness could matter and potentially contribute to the weekend effect. To determine the relevance of crowdedness for the weekend effect of reviews in these contexts, we use an external data source (Safegraph) that allows us to assess crowdedness for each business through an approximated number of daily visitors for each location. After carefully merging Yelp businesses with locations, we identified roughly 70,000 businesses with visitor data and sufficient coverage (see Web Appendix G). While we do find that relatively highly frequented places during the weekend show a larger weekend effect than businesses relatively highly frequented during the week, most importantly, for businesses that are equally busy during the week and weekend, there is still a significant weekend effect.

In another dataset (yourXpert), dates of the actual experience (i.e., consultation with a lawyer) are known, allowing us to assess whether the quality of what is reviewed changes between weekdays and weekends. We find no significant difference for week and weekend consultations ($M_{week} = 9.50$, $M_{weekend} = 9.51$, $t(7120) = -.19$, $p = .84$), but for timing of the review submissions, the platform shows the usual weekend effect (see Table 1).

In summary, we find no evidence that quality fluctuations are responsible for the weekend effect. The special case of crowdedness might exacerbate the weekend effect, but only in contexts where crowdedness is relevant, which is only in 6 of our 33 datasets (i.e., those focused on restaurants and travel such as Yelp).

Between listings – Different listings being reviewed. If the listing (e.g., a product, business, or employer) reviewed on weekends tend to be systematically of lower quality, this could potentially explain the observed weekend effect. Several pieces of evidence challenge this explanation.

After we control for listing fixed effects, the weekend effect loses its significance for only 2 of the 26 platforms that initially showed the effect (see Table WD1)—namely Trustpilot and OMR Reviews, which are among the platforms with the fewest reviewed listings in our dataset (i.e., around 250 shops for Trustpilot and 1,000 types of software on OMR Reviews, see Table WC1).

It could also be that on a weekend, less popular listings, i.e., products with a systematically lower review volume or lower average review valence, are being reviewed, thereby triggering users to submit a lower rating. These time-variant characteristics of a listing are not controlled for through fixed effects. Therefore, in the regression displayed in Table 2, we controlled for review volume and review valence in *t-1,* as users might have seen it when they submitted the review in *t*. Also, with the inclusion of these variables, the weekend effect remains relevant for 25 out of the 26 platforms (see Table 2).

The persistence of the weekend effect under the described conditions suggests that it cannot be universally explained by differences in listing quality, instead implying other factors contributing to lower ratings on weekends.

Reviewer-Specific Explanations

Beyond the characteristics of *what* is being reviewed, *who* submits the review, i.e., characteristics of the reviewers, could help explain the weekend effect. We examine and discuss potential within-reviewer explanations such as reviewers having more time to write on weekends, a tendency to delay writing negative reviews until the weekend, and higher expectations for weekend experiences. For between-reviewer explanations, we observe that different reviewers are more likely to submit reviews on weekends compared to weekdays, a phenomenon we refer to as "temporal self-selection."

Within reviewer – More time to reflect. Since people typically have more free time on weekends, one might expect them to have more time to reflect critically on their experiences, potentially leading to less favorable and more detailed reviews compared to those written during the typically busier weekdays. It is known that online reviews with a higher star rating tend to have a shorter text (Ullah et al. 2016), suggesting that reviewers feel the need to provide more detailed explanations when leaving a 1-star rating (Ghasemaghaei et al. 2018). Upon testing two of our datatsets, this was confirmed (Amazon: $Corr_{\text{Rating, Word Count}} = -.09$, $p <$

.001; Yelp: $Corr_{Rating, Word Count} = -.20$, $p < .001$). However, contrary to this expectation, weekend reviews—despite being generally more negative—do not necessarily contain longer text, as we find mixed results across Amazon and Yelp, with both platforms showing a weekend effect (see Table 1). On Yelp, reviews submitted on weekends tend to have fewer words ($M_{week} = 107.24$; $M_{weekend} = 100.70$), shorter sentences ($M_{week} = 13.50$; $M_{weekend} = 13.01$), and show lower signs of cognitive involvement ($M_{week} = 9.19$; $M_{weekend} = 8.98$). For Amazon, this is reversed (Word Count: $M_{week} = 48.32$, $M_{weekend} = 48.86$; Words-per-sentence: $M_{week} = 11.05$, $M_{weekend} = 11.09$; Cognitive Processes: $M_{week} = 9.79$, $M_{weekend} = 9.80$).

Moreover, if reviewers were taking more time to write on weekends, we might expect a higher proportion of reviews submitted via desktop rather than mobile devices. But data from TripAdvisor contradict this: During weekends, there is a lower proportion of desktop submissions (92.3%) compared to weekdays (94.9%).

In summary, it is difficult to test whether online reviews during the weekend are worse due to users having more time to reflect. Collectively, findings from our secondary data using different proxies regarding this explanation show no strong evidence for reviewers engaging in deeper reflection when writing reviews on weekends.

Within reviewer – Delaying negative reviews. People might wait until the weekend to write negative reviews, as they generally have a tendency to procrastinate doing unpleasant tasks (Pychyl et al. 2000). However, past research demonstrated a *fading affect bias*, which implies that people forget negative memories more quickly than memories related to positive emotions (Walker, Skowronski, and Thompson 2003). Furthermore, research documents a positivity bias for temporally distant events (Eyal et al. 2004; Herzog, Hansen, and Wänke 2007). Both these theoretical accounts would predict that if people postpone writing certain reviews to the weekend, those reviews should be positively biased. And indeed, empirical research supports this. Reviews for rather temporally distant events (i.e., the event happened some time ago) tend to be more positive (Huang et al. 2016; Neumann, Gutt, and Kundisch 2022). In most of our secondary data, we cannot assess the time that passed between the actual experience and the writing of the online review. Exceptions are TripAdvisor and yourXpert, where the time passed is 1.24 months and 9.66 days respectively.

To test whether people delay writing their negative reviews, we compare the time elapsed since the experience for reviews written during the week versus those written during the weekend. For both platforms, results of a two-sided t-test showed no significant difference (TripAdvisor: $M_{\text{Week reviews}}$ = 1.20 months; $M_{\text{Weekend reviews}}$ = 1.16 months; $t(90378) = 1.94$; $p = .053$; yourXpert: $M_{\text{Week reviews}}$ = 14.28 days; $M_{\text{Weekend reviews}}$ = 17.54 days; $t(444) = -.84$; $p = .403$). This suggests that the explanation for the weekend effect seems not to be driven by people delaying sharing negative experiences to the weekend.

Within reviewer – Higher expectations. Another explanation for worse reviews on weekends could be that there are different expectations on weekdays and weekends. Elevated expectations during weekends may stem from their association with leisure, relaxation, and the desire to maximize the value of this rare, work-free time. Given that experiences are evaluated relative to expectations, the heightened standards associated with weekends may lead to more negative perceptions of experiences that fail to meet the elevated expectations.

The desire to make optimal use of the limited weekend time may manifest in engaging in different activities compared to weekdays. We have ruled out that the weekend effect is caused by this explanation in the “between listings” explanation above, where we showed that the weekend effect is not driven by different listings being predominantly reviewed during the weekend. Moreover, we showed that the weekend effect persists when controlling for a business’s previous rating and review volume, which can be seen as a proxy for the quality and popularity of the business and thus related to expectations of the product or experience (see Table 3). Two datasets allow for an additional analysis related to price as a reflection of expectations. In Yelp, some businesses denote a price range (i.e., $, $$, $$$, or $$$$) for their services, and Sephora lists the price of reviewed products (in US$). For Yelp the average price of reviewed businesses during both the week and weekend is between $ (= 1) and $$ (= 2) (namely, 1.89), and for Sephora products reviewed during the weekend, prices are lower compared to weekday reviews ($M_{\text{week reviews}}$ = 49.30 US$, $M_{\text{weekend reviews}}$ = 48.07 US$; $p < .001$). This again confirms that on the weekend it is not the case that more upscale or expensive targets are being reviewed for which users may hold higher expectations.

Generally, like the previous crowdedness account, different expectations appear to be relevant only for the category of travel, restaurants, and experiences. For products and employers, one would not expect weekend reviewers to have higher expectations. Using available proxies, we find no consistent evidence that different expectations of consumers between the week and weekend can explain the weekend effect.

Between reviewers – Temporal self-selection. Drawing on the literature of self-selection, particularly intertemporal self-selection, we conjectured that different types of reviewers could choose to write on weekends versus weekdays, leading to systematic differences in online reviews and ratings. To investigate this possibility, we define three types of reviewers: weekday reviewers, who submit reviews only during the week; mixed reviewers, who submit both during the week and weekend; and weekend reviewers, who submit reviews only on the weekend. When averaging across all our datasets, we find that on average every sixth reviewer reviewed only during the weekend (17%). A little more than half of reviewers reviewed only during the week (64%), and the rest are mixed reviewers who reviewed both during the week and weekend (19%). To understand whether the weekend effect is driven more strongly by this temporal self-selection of reviewers or by differences within reviewers, we compare the three groups and their ratings submitted during the week and weekend (see Table 5).

Table 5 shows that the within-reviewer effect (i.e., the difference of review ratings submitted by mixed reviewers during the week and weekend) is generally smaller ($M_{\text{within-reviewer effect}}$ = .027) than the difference between the ratings of online reviews submitted by pure week and weekend reviewers ($M_{\text{temporal self-selection}}$ = .053) and less consistent across platforms (Temporal self-selection: 63% of platforms; Within-reviewer effect 46% of platforms).

Platforms	% Week reviewers	% Mixed reviewers	% Weekend reviewers	Average rating from…				Temporal self-selection	Within-reviewer effect
				Week reviewers	Mixed reviewers: *During week*	Mixed reviewers: *During weekend*	Weekend reviewers		
kununu	86	2	12	3.73	3.32	3.19	3.38	-.35***	-.13***
HelloPeter	90	2	8	3.27	2.73	2.72	3.19	-.08*	-.01
Skytrax	71	7	22	3.91	5.05	4.92	3.63	-.28***	-.13*
Trustpilot	81	0	18	3.97	3.29	3.13	3.89	-.08***	-.16*
BaSalam	82	12	6	4.50	4.56	4.50	4.41	-.09***	-.06***
Sephora	68	13	19	4.26	4.28	4.27	4.20	-.06***	-.01
OMR Reviews	98	1	1	8.86	8.35	8.35	8.95	.09	-.00
Luxxify	70	9	21	4.41	4.37	4.36	4.35	-.06***	-.01
Google	65	13	22	4.13	4.02	4.01	4.06	-.07***	-.01***
Walmart	73	4	23	4.19	3.95	3.96	4.16	-.03*	.01
LibraryThing	52	35	13	4.04	3.83	3.83	4.02	-.02	.00
IMDb	55	20	25	7.03	7.37	7.35	6.96	-.07***	-.02
TripAdvisor	56	27	17	4.04	4.19	4.16	4.00	-.04***	-.03***
Dianping	47	40	13	3.54	3.64	3.61	3.41	-.13***	-.03***
Yelp	54	23	23	3.59	3.71	3.66	3.55	-.04***	-.05***
Apple Podcasts	74	10	16	4.74	4.58	4.57	4.74	.00	-.01**
Goodreads	34	58	8	4.12	4.00	3.99	4.13	.01*	-.01*
Amazon	57	28	15	4.05	4.16	4.14	4.02	-.03***	-.02***
My Anime List	56	22	22	7.64	7.47	7.44	7.64	.00	-.03
BeerAdvocate	40	47	13	4.00	3.89	3.89	3.95	-.05**	.00
RateBeer	47	38	15	14.50	13.69	13.70	14.53	.03	.01
RottenTomatoes	62	14	24	3.85	3.82	3.83	3.86	.01**	.01*
Coursera	64	15	21	4.72	4.68	4.69	4.72	.00	.01**
Edmunds	64	17	20	4.17	4.18	4.19	4.24	.07***	.01

Notes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$. For platforms such as Olist, Glassdoor, Indeed, yourXpert, WebMD, Drugs.com, Steam, Booking.com, and Jameda, the absence of a user-specific variable in the datasets prevented us from conducting this analysis. The unit of analysis is a reviewer.

Table 5: Week, Mixed, and Weekend Reviewers in our Datasets

We conducted the following additional robustness analyses within the Amazon dataset: The temporal self-selection remains significant also in a subset of users that have submitted at least two reviews ($M_{\text{temporal self-selection}}$ = -.02, $p < .001$), when looking at only the three categories within Amazon that have shown the strongest weekend effect (i.e., "software", "patio, lawn, and garden", and "videogames"; $M_{\text{temporal self-selection}}$ = -.08, $p < .001$) and holding the product being reviewed constant ($M_{\text{temporal self-selection}}$ = -.05, $p < .001$).

To better understand this temporal self-selection, i.e., different reviewers writing reviews during the week versus the weekend, we explore how weekend reviewers differ from weekday reviewers by comparing the two groups based on the limited information available in our secondary datasets regarding reviewer characteristics. In addition, we analyze the review texts themselves. Prior research suggests that language can serve as a window into the reviewer's identity (Park et al. 2015), potentially revealing systematic differences between the two groups. We focus our text analysis on one of the major review platforms: Amazon. We do so to hold product quality constant, as it cannot fluctuate throughout the week, as in restaurants, for example. To further ensure stability regarding what is being reviewed, we focus our attention again on the three categories that show the largest weekend effect within Amazon (i.e., "software" (weekend effect = -.05), "patio, lawn, and garden" (weekend effect = -.04), and "videogames" (weekend effect = -.04). These categories were selected because they show the strongest weekend effects, allowing for a more focused investigation into the characteristics of weekend versus weekday reviewers who drive the observed differences. However, it is important to acknowledge that this selection based on effect size limits the generalizability of our findings.

We compare the text of the week and weekend reviewers using LIWC (Pennebaker, Booth, and Francis 2001), which is a widely used dictionary-based software for analyzing written text (Hartmann et al. 2019). We focus on the four categories of "Psychological Processes" (i.e., Cognition, Affect, Social, and Perception) to explore potential processes that reviewers might engage in when submitting an online review. The LIWC scores we report represent the percentage of words in a given review that fall into each category, thereby normalizing for differences in review length. We see that weekend reviewers tend to use less words belonging to the Social category in LIWC ("LIWC: Social"; $M_{\text{week reviewers}} = 6.25$, $M_{\text{weekend reviewers}} = 6.16$, $p < .001$). Words related to social process in LIWC indicate social interactions (e.g., talk, share, meet), family, and friends. Findings of past studies suggest that the use of this group of words relates to social connections and closeness (Pressman and Cohen 2007; Stone and Pennebaker 2002). Thus, the consistently lower use of words relating to social processes suggests lower social connections and closeness of weekend reviewers, based on the language used in their reviews compared to weekday reviewers.

We also find a significant difference in the use of mentions related to Affect ("LIWC: Affect"; $M_{\text{week reviewers}} = 12.96$, $M_{\text{weekend reviewers}} = 12.87$, $p < .001$). Within affective processes ("Affect") we find the starkest difference for mentions related to sadness (LIWC: "emo_sad"), with more sadness coming from weekend reviewers' reviews: $M_{\text{week reviewers}} = .097$, $M_{\text{weekend reviewers}} = .106$, $p < .001$). For the remaining categories we find no evidence for differences in other psychological processes, such as a cognitive ("LIWC: cogproc", $M_{\text{week reviewers}} = 9.94$, $M_{\text{weekend reviewers}} = 9.94$, $p = .43$) or perceptual process ("LIWC: Perception", $M_{\text{week reviewers}} = 7.40$, $M_{\text{weekend reviewers}} = 7.40$, $p = .71$).

The differences for the category related to social processes ("Social") as well as the category of mentions related to sadness ("emo_sad") remain significant when holding the product constant (i.e., for each product we compare the average across its reviews from week and weekend reviewers): "LIWC: Social", $M_{\text{week reviewers}} = 6.23$, $M_{\text{weekend reviewers}} = 6.17$, $p = .01$; "LIWC: emo_sad", $M_{\text{week reviewers}} = .113$, $M_{\text{weekend reviewers}} = .118$, $p = .04$.

Finally, if the observed differences in how weekday and weekend reviewers write their reviews reflect underlying differences between these groups, we would expect such differences to be absent in the reviews of mixed reviewers who submit on both weekdays and weekends. To test this, we build random datasets of equal size of 1 million reviews each from week reviewers, weekend reviewers, and mixed reviewers including their week and weekend review texts from the previous dataset. Comparing the week and weekend reviews, we find that the psychological driver in LIWC of "Social" processes is indeed not statistically different between mixed reviewers' week and weekend reviews ("LIWC: Social"; $M_{\text{week reviews}} = 5.90$, $M_{\text{weekend reviews}} = 5.90$, $p = .70$). Regarding the emotion of sadness, in the texts of mixed reviewers, we find that whereas there are still slightly more mentions related to sad words during the weekend (LIWC: "emo_sad"; $M_{\text{week reviews}} = .072$, $M_{\text{weekend reviews}} = .077$, $p < .01$), this difference is smaller than the difference of week and weekend reviewers ($M_{\text{week reviewers}} = .097$, $M_{\text{weekend reviewers}} = .106$, $p < .001$). These results allow us to further speculate about the smaller and less consistent weekend effect among mixed reviewers. The within reviewer explanations we tested, such as differences in expectations, do not account for this pattern, though the slight increase in sad language on weekends may reflect subtle situational influences. One possibility is mood congruence, where a reviewer's emotional state at the time of writing influences tone. While speculative, this interpretation aligns with the observed text difference.

Building on our findings regarding textual cues of lower social connectedness of weekend reviewers, we investigate potential differences between the two types of reviewers regarding the number of friends on online platforms. This information is only available in two of our datasets that include a social network: Yelp and Dianping. On both, we find that weekend reviewers have significantly fewer friends than week reviewers (one friend less on Dianping, $p < .05$; three friends less on Yelp, $p < .001$). This is in line with lower mentions of social processes in weekend reviewers' texts. Moreover, results from a subsequent survey among actual Yelp reviewers suggest that the number of friends on Yelp is a valid proxy for real-life friends and correlates with how lonely and socially connected Yelp reviewers are (see Web Appendix H).

Hence, we find consistent evidence that weekend reviewers tend to submit online reviews with lower ratings compared to the group of week reviewers (see Table 5, column "Temporal self-selection"), and that the difference in ratings between these two reviewer groups is higher and more consistent than the difference within mixed reviewers' week and weekend ratings (see Table 5, column "Within-reviewer effect"). While week and weekend reviewers differ in their review texts, mixed reviewers show no week–weekend differences in social references and only smaller differences in sadness. Further, weekend reviewers have fewer online connections. Overall, our findings consistently suggest that weekend reviewers tend to experience higher levels of social disconnectedness compared to their weekday counterparts, consistent with literature on weekend loneliness (e.g., Akay and Martinsson 2009; Kavetsos, Dimitriadou, and Dolan 2014; Maennig, Steenbeck, and Wilhelm 2014). A survey we conducted of Yelp week, and weekend reviewers shows suggestive evidence in line with our findings that those active on weekends report feeling less socially connected and lonelier (Web Appendix H).

Taken together, the explanation for which we find the most consistent support across multiple data sources and methods is a reviewer related explanation, namely temporal self-selection referring to differences between reviewers reviewing during the week or on weekends. While other potential explanations such as variation within reviewers between week and weekend reviews, contextual influences like crowdedness, or category specific effects may also play a role, they receive less consistent empirical support or appear limited to specific contexts. Overall, temporal self-selection appears to be the most broadly applicable explanation of the weekend effect, even though other contributing factors cannot be entirely ruled out.

Managerial Implications

The weekend effect may have significant implications for businesses reviewed online, which, in today's digital landscape, encompasses virtually all businesses. We first provide evidence for why the weekend effect is meaningful and relevant. Then we show with five studies (including two field experiments) that businesses seeking to collect reviews can mitigate the weekend effect of reviews through strategic review management and more specifically by restricting the timing of online review solicitations to weekdays.

The Relevance of the Weekend Effect for Businesses

Across our datasets, we find an average weekend effect of .04 stars. Even if this effect seems small at first glance, it still matters. We demonstrate this by examining the weekend effect in online reviews, focusing on i) its implications for the long tail, ii) its influence on rankings, iii) the impact of single negative reviews more likely to arrive during weekends, iv) the magnitude of observed effects in online review research, and v) its approximated economic significance.

i) The relevance of the weekend effect for the long tail. Listings on online review platforms tend to follow a long-tail distribution (i.e., a few products with strong sales and many products for which only a few are sold) (Anderson 2006; Brynjolfsson, Hu, and Smith 2006; Oestreicher-Singer and Sundararajan 2012). Because the number of online reviews each listing has is a function of sales, the number of online reviews per listing also follows a long-tail distribution (i.e., a few listings with many reviews and vice versa). For example, on Amazon the median number of reviews per listing is 3, while the mean is 22, offering evidence for a long-tail distribution. A single negative review (which we show is more likely to be submitted during the weekend) is especially detrimental to the average rating of a listing that so far has accumulated only a few reviews. Thus, for a typical product on Amazon with 3 reviews and an average rating of 4.00 stars, a new 1-star review would alter the average rating from 4 to 3.25 stars.

To more systematically assess the impact on the average rating and implications for the long tail, we measured how frequently listed products experience at least a half-star improvement if there were no weekend reviewers. From prior literature, we know that such a half-star improvement is associated with a substantial demand impact (e.g., Anderson and Magruder 2012; Luca 2011; Magnusson 2022). We focused on products as here the quality is stable. We calculated each listed product's average rating in two ways: first, using all reviews; and second, excluding reviews from weekend reviewers. Our goal was to assess how often a product's average rating improves by at least .5 stars under the latter condition. As expected, we find that products with fewer reviews are more susceptible to the influence of weekend reviewers. Figure 4 shows that up to 6% of products with only 3–4 reviews would experience a half-star increase in their average rating if weekend reviewers were excluded. This percentage increases to more than 8% for Amazon products in the three categories with the biggest weekend effect from before.

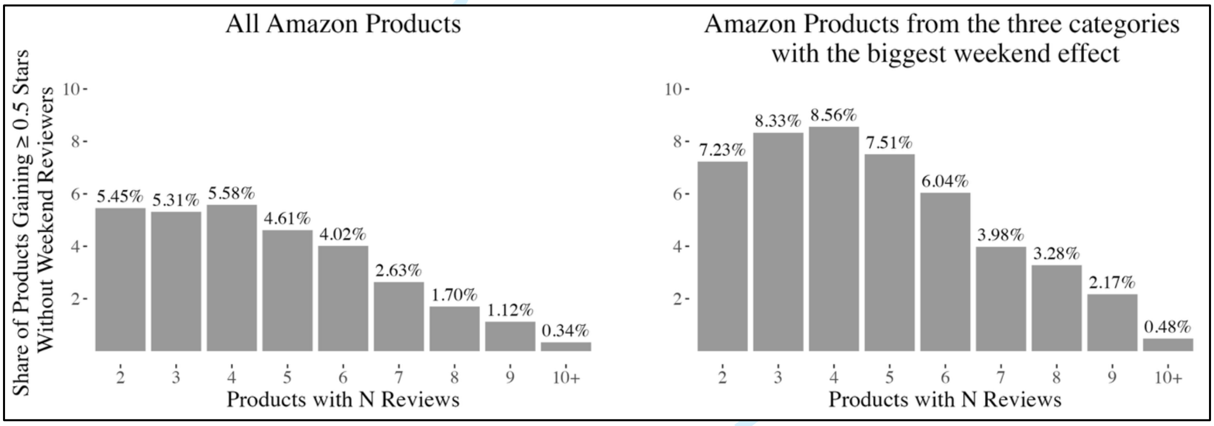


Figure 4: Share of Products Gaining Half a Star Without Weekend Reviewers (by Number of Reviews)

ii) The weekend effect and its impact on rankings. Given the potential impact of a single negative rating, the weekend effect can have important implications for rankings. Typically, online review platforms display listings ranked according to average ratings or use an internal sorting logic, which generally relies as well on a listing's average rating (Talton et al. 2019). For rankings based on the average rating, a decrease in the average rating of .75 stars – similar to the one described previously – can move a product from the 70^{th} to the 40^{th}

percentile, effectively shifting it from the top 30% to the bottom 40% of the platform.[1] This is because listings tend to be ranked very close to each other when considering their overall average rating. But even small rating differences can have drastic implications for how listings are ranked, how visible they are, and how much interaction they receive. Among 10 listings, 80%–90% of users viewed and 70% clicked on the top listing, while less than 10% viewed and clicked on the bottom listing (Demsyn-Jones 2022; Pan et al. 2007).

To visualize the effect, we demonstrate the influence of small rating differences on rankings in our data. We again focus on software products from Amazon, because unlike restaurants or other experiences, the underlying quality of reviewed software is arguably stable throughout a week. In our data we observe 1,962 products in this category that currently have 3 reviews, which is the median number of reviews in the software category. The products' median rating is 3.33 stars, and their ranking position is 938. If a fourth negative 1-star review is added to one of these products, which is 4.6%[2] more likely to happen during the weekend, its new average rating would be 2.75 stars, thereby downgrading this software from rank 938 to 1,114. Such a change in rank – 176 positions, or 8.9% on a list of 1,962 products – may result from a single additional negative review. Finally, to more systematically analyze differences in ratings, we compare how products would be ranked according to their weekday-only reviews versus their weekend-only reviews.[3] We observe that the two rankings differ significantly (Wilcoxon signed rank test with continuity correction: $p < .001$) and show only a medium correlation (Kendall's $\tau = .51$). Usual measures for comparing rankings such as Kendall's τ have the disadvantage that they are

[1] Among the 11,314 software products in our Amazon dataset with at least 3 reviews, the distribution of their average rating is as follows (in percentiles): P10: 2.10, P20: 2.60, P30: 3.00, P40: 3.23, P50: 3.50, P60: 3.67, P70: 3.95, P80: 4.19, P90: 4.50 stars.
[2] Percentage of 1-star reviews during the week (weekend): 22.08% (23.11%). Thus, 23.11 / 22.08 = 1.046.
[3] We do this for Sephora, as it is a platform where the underlying quality of what is being reviewed is stable (product quality does not change throughout the week) and because it allows us to keep the items that are being reviewed fairly stable (only Beauty products).

unweighted, placing as much emphasis on the disagreement of two rankings at their top as at their bottom. Therefore Webber, Moffat, and Zobel (2010) proposed an improved similarity measure, which they call rank-based overlap (RBO), that is especially suited for instances such as search engines or online review platforms where results at the top matter more than results at the bottom. This is important, as users usually do not read beyond the first page. According to this measure, the two rankings are even more dissimilar (*rbo* = .15).

iii) The impact of a single review. Certainly, for the few listings that have accumulated many reviews, a single bad review might have less of an impact on the average rating. Nonetheless, it has been shown that not only is the average rating important for consumers' decisions, but individual reviews also can have a strong effect on decisions (Vana and Lambrecht 2021), especially negative reviews (Varga and Albuquerque 2023). Thus, the threat of a single negative review displayed as the most recent online review becomes more imminent around weekends.

iv) Effect sizes in online review research. Small effect sizes in online review research have been widely observed and can be expected due to the skewness of online ratings and the strong tendency of reviewers to give 5-star ratings (Brandes, Godes, and Mayzlin 2022; Schoenmueller, Netzer, and Stahl 2020). Brandes and Dover (2022) report that ratings drop by .1 stars when it rains, Bayerl et al. (2024) find that women's ratings average is .08 stars higher than men's, and Bairathi, Lambrecht, and Zhang (2023) show that female freelancers receive ratings .01 stars lower than male freelancers.

v) Approximating economic significance. For the 26 platforms for which we find a weekend effect (see Table 1), a comparison of the NPS of all online reviews submitted during the weekend versus during the week shows a lower NPS for weekend reviews by .2 to 19.5 points (see Table WC1). Across these datasets, the NPS from weekend reviews is 3.6 NPS points lower compared to weekday reviews. Marsden, Samson, and Upton 2005 showed that a higher NPS is associated with more future growth and sales: In their analysis, each 1-point difference in NPS relates to a .147% revenue growth for the average business in their analysis. Thus, transferring the differences into monetary value shows the potential importance of the weekend effect in terms of sales. According to the result of Marsden, Samson, and Upton (2005), a weekend effect corresponding to a .2- to 19.5-point lower NPS across platforms relates to a .07% to 2.9% lower revenue growth.

In summary, the weekend effect of online reviews, despite seeming small in absolute magnitude, has economic significance and consequences for businesses. In the following sections, we present five additional studies that illustrate how companies can leverage our findings to strategically adjust the timing of review solicitations, thereby actively incorporating insights related to the weekend effect.

Leveraging the Findings of the Weekend Effect

Building on our findings, we conducted five studies to investigate its practical implications for companies. These studies reveal that soliciting reviews during the weekend leads to a higher proportion of negative feedback. By understanding this pattern, companies can strategically adjust their review solicitation timing to mitigate unfavorable outcomes.

Study 1: Soliciting via email. We build on a dataset of employer reviews for which we can identify a review solicited via email. For a subset of 282,881 employer reviews from our kununu dataset, we can assess whether users wrote a review after having received an email from the platform asking them to do so. Comparing only solicited reviews and solicited week reviews, we find the "weekend effect" pattern: Weekend reviews ($n = 17{,}875$, $M = 3.69$) are significantly less favorable than weekday reviews ($n = 265{,}006$, $M = 3.86$, $t(20{,}008) = 18.83$, $p < .001$). This finding suggests that the weekend effect is not limited to unsolicited reviewing behavior but also appears in solicited reviews – indicating that the mere timing of review solicitation may influence review valence. A limitation in this study is that we can only infer the time the review was written, not the time the email was sent.

Study 2: Soliciting via social media ads. For a set of 76,323 employer reviews, we know that users were triggered to write the review through a social media ad. Similar to the previous study, we don't know when reviewers were exposed to the social media ad, but it seems very unlikely that someone clicked on a social media ad during the week and kept the window open only to then review during the weekend. Thus, in this dataset it's highly likely that the exposure to the solicitation and the submission of the review coincided on the same day. We find again that weekend reviews (n = 14,572, M = 3.42) are significantly less favorable than weekday reviews (n = 61,751, M = 3.59, t(21,694) = 14.01, $p < .001$). Thus, the result confirms in a different setting that the weekend effect is present even in solicited reviews, suggesting that the timing of solicitation may influence review valence. Both studies are in the context of employer, job, and workplace reviews, which is the category with the largest weekend effect. In the following we assess whether soliciting during the week versus the weekend matters in other contexts.

Study 3: Soliciting via emails. In our dataset from yourXpert, we know when the actual experience (i.e., the consultation with a lawyer) took place. Upon discussion with the platform, we learned that it sends an automated email reminding users to review 2 days after the experience took place and for a period of time, they sent another additional reminder after 14 days. 40% of reviews (n = 11,796) are written either on or the day after the experience, for the remaining 60% (n = 17,502), we assume that they were solicited through the email. This seems a sensible approach, as the data clearly shows peaks in review volume when solicitation emails are sent. Despite the small sample size compared to the previous studies our regression analysis still shows that ratings are, on average, .046 stars lower (SE = .027) when the solicitation email is sent on the weekend ($p = .088$), while controlling for whether the review was triggered by the first or the second reminder email. A limitation of this study is that the date when the email was sent was not randomized. It could be that users who consulted a legal expert on Thursday or Friday (and thus received the email on a Saturday and Sunday) are inherently different personas or were concerned with different, perhaps more difficult issues. At the same time, legal experts accepting a consultation closer to the weekend could differ along unobservable characteristics such as their experience. We go on to address these issues by conducting two A/B tests.

Study 4: An experiment with Prolific users. The aim of this study was to approximate an actual field setting in which users are randomly assigned to one of two conditions ("Week" and "Weekend") and are asked to submit a review. For random assignment to these two conditions, we conducted a longitudinal multi-part study through Prolific. In Part 1, we constructed a database of users, replicating the type of database a platform or business might maintain. We opened Part 1 in November 2024 to 1,000 Prolific users from the USA fluent in English. We made participants aware that we will reach out to them again within the following 10 days for the second part of the study. We randomly split the participants acquired in the first stage into two groups: 500 were invited on a Wednesday and 500 were invited on a Saturday for our Part 2, in which users submitted online reviews for any restaurant, software, and hotel (the order was randomized for each participant). On Wednesday 406 respondents took part (380 after attention check), and on Saturday 296 respondents took part (281 after attention check). A chi-square test of independence confirmed that significantly more participants responded on Wednesday (380) than on Saturday (281) ($\chi^2(1, N = 1000) = 42.86$, $p < .001$). Additionally, as expected with random assignment, there were no significant differences between the two initial groups of 500 participants in how they were assigned to receive Part 2 during the weekday or weekend ($p >$ .10) (see Table WI1 in Web Appendix I). However, differences emerged among those who actually chose to participate in Part 2 (see Table WI2). Specifically, participants from the weekend group reported marginally higher levels of social disconnectedness (M_{week} = 3.24, $M_{weekend}$ = 3.43, t(588) = 1.72, p = .09) and had submitted fewer past reviews (M_{week} = 5.46, $M_{weekend}$ = 4.23, t(658) = -2.43, p = .02). These patterns suggest that, despite random assignment, the individuals who chose to respond on the weekend differ systematically from weekday respondents — consistent with the broader notion of temporal self-selection, whereby different types of people are more likely to engage on different days.

For each user, we then averaged their three rating scores to build one average review rating per user. We know from our secondary data that the average weekend effect is -.04 stars (see Table 1) – we thus use this value as a comparison point. The results of our field study show a similar average weekend effect of -.05 stars (M_{week} = 4.12, $M_{weekend}$ = 4.07). Due to the modest effect size, a much larger sample size would be required to achieve statistical significance. A power analysis on the weekend effect across restaurants (Table 1: Yelp), software (Table 1: OMR Reviews), and hotels (Table 1: TripAdvisor) would have required at least 30,000 to 40,000 reviews. Consequently, the statistical power of this analysis is low and the difference is not statistically significant (two-sided t-test reveals a p-value of only .33, t(585) = -.97). In addition to the comparison of mean differences, we compare the two groups regarding the categories of detractors (all 1-, 2-, and 3-star reviews) and promoters (4- and 5-star reviews), similar to our secondary-data analysis. Implementing a chi-squared test of independence reveals a difference between the day of the week (Saturday vs. Wednesday) and review ratings (promoters vs. detractors) at a p-value of .06 (χ^2(1, N = 661) = 3.42). Although for technical reasons, our study can't have sufficient power to achieve strong statistical significance, the observed effect size is consistent with our secondary data, and it is common to see platforms collecting large amounts of reviews in one campaign.

While Study 4 replicates the weekend effect under randomized solicitation timing, our managerial implication is not to try to adjust the valence of weekend-written reviews. Rather, we demonstrate that strategically timing review solicitations can reduce the likelihood of weekend submissions, thereby avoiding the weekend effect altogether. Focusing review solicitation on weekdays can avoid triggering a segment of users that systematically is more likely to review negatively, thereby alleviating the weekend effect. In this way, the timing of solicitation serves as a practical lever to manage the tone of reviews. Study 5 provides further evidence for this effect using a real-world review platform.

Study 5: A field experiment. In collaboration with an online review platform (OMR Reviews), we conducted a preregistered field study (AsPredicted #189276). The platform provided access to 12,500[4] of their existing users and email addresses with marketing and outreach consent so we could solicit (without an incentive) half of the users on a Wednesday and the other half on a Saturday through an email similar to how the platform usually reaches out to its user base. We chose Wednesday and Saturday because on this platform these are the days with the highest/lowest average ratings based on our secondary data. The average rating of those who received the email on a Wednesday (Saturday) was 8.03 stars (7.61 stars). Unfortunately, only .6% of users converted to the review process (n = 70; such low conversion rates to writing an online review are the norm (Anderson and Simester 2014)). Thus, although we replicate the direction and the magnitude of the weekend effect in the preregistered direction, a two-sided t-test reveals a *p*-value of only .41 (t(64) = -.83). A power analysis shows that 3,000 respondents would have been required to reach significance. This number was beyond the capacity of the corporate partner in this study but is within a plausible range for campaigns collecting reviews. Thus, although our study lacks sufficient

[4] We preregistered 25,000 users. However, for internal business reasons, the corporate partner restricted the outreach to 12,500 users after our preregistration.

power to achieve statistical significance, the observed trend and effect size are again fully consistent with our secondary data.

In sum, the evidence from these five studies, despite their specific limitations, demonstrates the managerial relevance of the weekend effect. Our findings inform businesses how the mere timing of review solicitations can affect the subsequent review ratings and thus how the adjustment of the timing of review solicitations to weekdays can help avoid collecting negative weekend reviews. This complements work on optimal scheduling in social media content management, which shows that the timing of posts can significantly shape engagement (Kanuri, Chen, and Sridhar 2018). Beyond adjusting the timing of solicitations, our findings suggest that platforms should, where feasible, identify weekend reviewers based on existing reviewer histories. This approach would allow platforms to not only refine the timing of solicitations but also tailor the selection of targeted individuals to minimize negative effects of the weekend.

DISCUSSION

We find a persistent and robust weekend effect in almost 400 million reviews for more than 20 million reviewed listings from more than 60 million users. The data stem from 33 different datasets featuring a wide range of product and e-commerce, service and leisure, and workplace-related reviews. Ratings submitted during the weekend are significantly lower than those submitted during the week. Whereas weekend effects are a well-known phenomenon in other contexts, we introduce the weekend effect to marketing. Contrary to past findings (Dodds et al. 2011; Golder and Macy 2011) that show user-generated content (UGC)—in the form of social media postings—to be more positive on the weekend, we show the opposite for another form of UGC, online reviews.

We discuss potential explanations for this seemingly counter-intuitive effect. Between *where* (i.e., platform-related factors), *what* (i.e., listing related factors) and *who* (i.e., reviewer-related factors), it was especially the latter that seemed to be related to the weekend effect. More specifically, a temporal self-selection appears to be the most consistent explanation that plays a role across all platform categories. These findings contribute to the literature on online reviews by introducing a novel form of self-selection: a temporal self-selection, where during the weekend, a different set of users – those more prone to write negative reviews – is more likely to select to leave a review.

We highlight that the weekend effect contradicts the expectations of managers (see Web Appendix B), thereby challenging and reshaping prevailing paradigms. We further demonstrate the economic significance of the weekend effect. Finally, with five studies we show how businesses can actively use our results in the context of review solicitations.

Our findings also provide implications for platforms. Just as some platforms show the distribution of past ratings (e.g., searching for businesses on Google, users see how many 1-, 2-, 3-, 4-, and 5-star reviews a listing has), platforms might want to consider displaying ratings across days of the week to show patterns and potential biases. Platforms could even introduce a filter allowing separation between week and weekend reviews. The fact that online reviews differ by the day they are submitted while the underlying quality of what is reviewed remains stable is something platforms should consider moving forward.

In terms of limitations, while we find strong evidence for temporal self-selection as main explanation it may not be the only one and we can only speculate about why there is a temporal self-selection. For example, also crowdedness contributes to the weekend effect, but only in specific settings. We also observe within reviewer differences, that is, individual reviewers tend to write more negatively on weekends than on weekdays, but we find this effect to be less consistent and weaker overall compared to between-reviewer differences (temporal self-selection). Moreover, we observe differences across platform categories and discuss potential explanations for this. Future research could delve further into the magnitude of the weekend effect across platforms and investigate differences in greater depth, extending our findings. Additionally, we identify small differences between individual weekdays. While these differences are less consistent across platforms compared to the weekend effect, an inverted U-shape pattern appears for some platforms with Thursday as the day with the highest ratings (see, e.g., HelloPeter, Google, LibraryThing, IMDb, Dianping, Yelp, WebMD in Figure WC2). Although investigating within-weekday differences is beyond the scope of this paper, as our focus is on the weekend effect, understanding these specific day-of-the-week differences – as well as potential time-of-day effects – represents a compelling avenue for future research. Extending our findings to consider day-of-the-week effects in offline rating or judgment contexts could be another intriguing direction for further exploration. We hope this paper inspires additional work in these and related areas.

Finally, while we demonstrate the managerial implications of our findings through multiple studies, we acknowledge limitations related to their sample size. Future research could build on our results by conducting large-scale studies to test different review solicitation timings and message framings to further extend our findings.

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Web Appendix

The Weekend Effect in Online Reviews

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Table of Contents

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WEB APPENDIX A - Two Types of User-Generated Content (UGC)

	Online Reviews (e.g., Yelp etc.)	**Social-Media Postings** (e.g., Twitter, Facebook, Instagram)
Purpose	providing feedback and evaluation of a product, service or business[39,44]	wide range of topics such as sharing personal experiences, opinions, and updates[44]
Audience	potential customers who are researching a particular product or service[4,21]	a user's social network, which usually includes friends, family, and acquaintances[31]
What is it about?	reviewing or refereeing someone else[21]	writing about your own life[24,31]
Motives		
Altruism/Social Concern	yes[4,20,21,47]	
Archiving/Nostalgia		yes[31,39]
Attention seeking		yes[39]
Communication		yes[39,40,41]
Economic Incentives	yes[8,20,43,47]	
Emotion Regulation	yes[4,20,21]	
Emotional Support		yes[30]
Entertainment	yes[4,8,20,42]	yes[26,39]
Helping the company	yes[8,47]	
Impression Management	yes[4]	yes[26,40]
Information Sharing	yes[4]	yes[24,30,41]
Information Seeking	yes[4,20,42]	yes[26]
Involvement	yes[4,20,42]	
Personal identity/Self-presentation		yes[24,30,31]
Platform Assistance	yes[8,47]	
Quality assurance	yes[8,42,44]	
Reciprocity	yes[4,21,42]	yes[30]
Self-enhancement	yes[4,20,21,47]	
Social influence	yes[4,21]	
Socialization	yes[20]	yes[24]
Surveillance		yes[31]
Format	standardized format, usually with a numeric rating and specific sections for commenting on different aspects[21]	many different forms, including text, images, videos, and links[24.30]
User characteristics	customers who have already experienced the product or service[44]	everyone may engage in creating social-media postings[44]
Anonymity	Rather anonymous with usernames (usually different to real name)[4,21,47]	Rather identifiable (usually with real name)[40]
Timing	posted after a specific experience, such as using a product or service[21]	can be posted at any time[31]
Persistence	stored and easily searchable for a longer period[5,47]	may be more ephemeral and disappear quickly[41]
Tone & Objectivity	Usually rather objective, formal and informative[21]	can be more informal, emotional and subjective[26]
Accessibility	usually accessible to everyone[4,5,47]	may be restricted to certain users or groups[38,40]
Engagement	can sometimes lack engagement, as they are often read but not interacted with[47]	can generate more engagement through likes, shares, and comments[39]

Sources: For full reference list, see Web Appendix references at the end of this document. [4] (Berger 2014); [5] (Berger and Schwartz 2011); [8] (Bronner and de Hoog 2011); [20] (Hennig-Thurau, Walsh, and Walsh 2003); [21] (Hennig-Thurau et al. 2004); [24] (Kaplan and Haenlein 2010); [26] (Luo and Hancock 2020); [30] (Oh and Syn 2015); [31] (Pempek, Yermolayeva, and Calvert 2009); [38] (Stutzman, Capra, and Thompson 2011); [39] (Sung et al. 2016); [40] (Varnali and Toker 2015); [41] (Vázquez-Herrero, Direito-Rebollal, and López-García 2019); [42] (Wang and Fesenmaier 2004); [43] (Wu et al. 2020); [44] (Xiang et al. 2017); [47] (Yoo and Gretzel 2008)

Table WA1: Two types of User-Generated Content (UGC)

WEB APPENDIX B - Survey about Counter-intuitiveness with Managers

To better demonstrate the lay beliefs or common expectations about the weekend effect, we surveyed 46 MBA students and 28 employees (managers with varying role titles) of an actual online review platform. The MBA students are representative of managers perhaps seeking to collect online reviews for their products or businesses. The online review platform employees are experts on the topic. We first asked on which days of the week participants (n = 74) would think that the most positive reviews are submitted. A higher percentage than one would expect by chance alone chose weekend days for the answer. By chance alone, 29% (2 out of 7) would pick a weekend day as the most likely time for the best reviews to be submitted, but in fact, more than 40% of those we surveyed thought a weekend day would offer the most favorable reviews. The results did not differ in a meaningful way between the two groups (MBA students and review platform employees). Interestingly, even the online review platform employees were not aware of the typical weekend effect that in fact exists for the review platform where they are employed.

We continued by asking on which day of the week participants (n = 76) expected the best conversion rate would be obtained for collecting online reviews through social media or email campaigns. Here the results differed between groups. MBA students expected higher conversion rates during the weekend, and online review platform employees expected rather lower conversion rates during the weekend. A typical manager would expect an email or social media campaign to be especially successful when conducted during the weekend. However, not only is this assumption about higher conversion rates during the weekend not true—if one trusts the intuition of the expert employees—it would also lead to the manager collecting especially bad reviews.

Given the results that reviews on weekends were expected to be more favorable than reviews written during the week, we propose that our findings (that actually the opposite is true) sketch the outline of an interesting and counter-intuitive phenomenon.

WEB APPENDIX C - Additional Information on Datasets

Platforms	#Reviews	#Review targets	#Users	Geographic focus in our dataset	Timeframe of our data	What is reviewed	Scale points	Intervals	Variance in ratings (Week/Week-end)	NPS Score (Week/Week-end)	Ratio of weekday to weekend according to: Google Trends Volume	Ratio of weekday to weekend according to: Review Volume	Polarity	Positive imbalance	Age of platform (years)	Type of Business Modell	Reviewer Soc. Network	Recognition System	Verified Reviews Enabled	Response to Reviews Supported
kununu	1.3 M	0.2 M	1 M	DACH region	2007 - 2021	Employers	1-5	Cont.	1.59/1.85	1.2/-18.3	1.76	2.71	0.45	0.72	17	Information	No	Yes	No	Yes
Olist	0.1 M	32 k	Unkn	Brazil	2016 - 2018	Products	1-5	1-star	1.67/2.08	37.9/28.8	2.65	1.24	0.69	0.85	9	Selling Products/Services	No	Yes	Yes	Yes
HelloPeter	56 k	68	49 k	South Africa	2015 - 2022	Shops	1-5	1-star	3.10/3.22	-4.0/-9.4	1.93	3.94	0.73	0.54	24	Information	No	No	No	Yes
Skytrax	0.4 M	2 k	0.1 M	Unkn.	2002 - 2024	Airlines	1-10	1-star	12.03/12.00	-37.9/-41.7	1.05	1.27	0.64	0.42	25	Information	No	No	Yes	No
Trustpilot	1.2 M	0.2 k	0.4 M	Unkn.	2007 - 2024	Shops	1-5	1-star	1.57/1.74	60.8/55.2	1.28	1.09	0.85	0.87	17	Information	No	Yes	Yes	Yes
BaSalam	3.4 M	0.7 M	0.9 M	Iran	2018 - 2024	Products	1-5	1-star	0.85/1.00	68.5/63.7	1.01	1.69	0.82	0.95	9	Selling Products/Services	No	No	No	Yes
Sephora	1.1 M	2 k	0.5 M	Unkn.	2008 - 2023	Beauty	1-5	1-star	1.28/1.43	46.8/43.3	0.82	1.28	0.69	0.89	21	Selling Products/Services	No	Yes	Yes	No
OMR Reviews	34 k	2 k	14 k	Germany	2020 - 2023	Software	1-10	1-star	2.40/2.51	52.6/45.8	2.15	10.20	0.61	0.98	5	Information	No	No	No	No
Luxxify	57 k	1 k	31 k	Unkn.	2010 - 2024	Beauty	1-5	1-star	1.27/1.42	51.6/48.9	0.76	1.23	0.73	0.89	17	Selling Products/Services	No	Yes	No	Yes
Glassdoor	10.7 M	40 k	Unkn.	Unkn.	2008 - 2023	Employers	1-5	1-star	1.54/1.57	-14.3/-17.8	2.00	1.73	0.37	0.75	16	Information	No	Yes	No	Yes
Google	10.4 M	3.0 M	4.6 M	Mainly USA	2010 - 2014	Businesses	1-5	1-star	1.44/1.41	25.5/20.1	0.91	1.01	0.56	0.85	17	Information	No	Yes	No	Yes
Walmart	59 k	43 k	8 k	USA	2009 - 2019	Products	1-5	1-star	1.85/1.93	42.8/40.2	0.88	2.00	0.75	0.83	16	Selling Products/Services	No	Yes	Yes	No
Indeed	1.0 M	0.5 k	Unkn.	Unkn.	2011 - 2023	Employers	1-5	1-star	1.35/1.39	-3.3/-5.1	1.61	1.70	0.39	0.82	13	Information	No	Yes	No	Yes
Librarything	1.4 M	0.4 M	0.1 M	Unkn.	2005 - 2013	Books	1-5	0.5-star	1.00/1.00	2.1/-0.5	1.96	1.00	0.33	0.89	19	Information	No	Yes	No	No
yourXpert	30 k	Unkn.	Unkn.	Germany	2012 - 2024	Lawyers	1-10	1-star	2.31/2.62	85.3/83.3	1.70	1.56	0.92	0.97	13	Selling Products/Services	No	No	Yes	Yes
IMDb	1.2 M	40 k	0.2 M	Unkn.	1998 - 2023	Movies	1-10	1-star	4.90/4.66	0.6/-2.9	0.80	0.72	0.32	0.90	23	Information	No	Yes	No	No
TripAdvisor	3.6 M	4 k	0.6 M	USA	2002 - 2012	Hotels	1-5	1-star	1.34/1.34	14.4/11.2	0.95	0.99	0.56	0.89	23	Transaction Fee	Yes	Yes	No	Yes
Dianping	5.4 M	0.2 M	0.5 M	China	2003 - 2013	Restaurant	1-5	1-star	0.74/0.78	-24.6/-25.8	1.00	1.08	0.17	0.90	11	Information	Yes	Yes	Yes	Yes
Yelp	6.9 M	0.2 M	2 M	USA, CAN	2005 - 2022	Businesses	1-5	1-star	2.18/2.20	13.7/12.3	1.10	0.86	0.62	0.74	20	Information	Yes	Yes	Yes	Yes
Apple Podcasts	5.3 M	3.1 M	0.3 M	Unkn.	2005 - 2023	Podcasts	1-5	1-star	1.03/1.10	77.9/76.5	1.41	1.54	0.93	0.92	7	Information	No	No	No	No
WebMD	0.5 M	8 k	Unkn.	USA	2007 - 2024	Drugs	1-5	1-star	1.61/1.64	-10.3/-11.2	1.06	1.21	0.40	0.70	19	Information	No	Yes	No	No
Drugs.com	0.2 M	4 k	Unkn.	USA	2008 - 2017	Drugs	1-10	1-star	2.11/2.15	15.0/14.7	1.82	1.20	0.66	0.73	23	Information	No	Yes	No	No
Steam	37.9 M	8 k	Unkn.	Unkn.	2010 - 2023	Videogames	+/-	/	0.11/0.11	74.4/74.0	0.85	0.86	/	0.87	11	Transaction Fee	Yes	Yes	No	No
Goodreads	14.2 M	1.2 M	0.4 M	Unkn.	2011 - 2015	Books	1-5	1-star	1.07/1.08	6.0/5.3	1.05	1.06	0.38	0.88	17	Information	Yes	Yes	No	No
Booking.com	0.5 M	2 k	Unkn.	Unkn.	2015 - 2021	Hotels	1-10	Cont.	0.52/0.51	35.3/34.9	1.05	1.11	0.48	0.97	23	Transaction Fee	No	No	Yes	Yes
Amazon	230 M	14.9 M	43.2 M	Unkn.	1996 - 2008	Products	1-5	1-star	1.54/1.56	43.7/43.5	1.03	1.18	0.72	0.86	29	Selling Products/Services	Yes	Yes	Yes	Yes
My Anime List	0.1 M	8 k	47 k	Unkn.	2006 - 2019	Animes	1-10	1-star	5.27/5.26	10.3/10.2	0.84	0.89	0.43	0.85	18	Information	Yes	Yes	No	No
BeerAdvocate	1.6 M	66 k	34 k	Unkn.	1996 - 2012	Beer	1-5	0.5-star	0.52/0.51	8.1/8.0	0.76	0.91	0.27	0.95	24	Information	No	Yes	No	No
RateBeer	2.9 M	0.1 M	29 k	Unkn.	2000 - 2012	Beer	1-20	1-star	11.34/10.98	-28.3/-28.4	0.90	0.85	0.07	0.88	24	Information	Yes	Yes	No	No
RottenTomatoe	55.1 M	10 k	8.8 M	Unkn.	1996 - 2024	Movies	0.5-5	0.5-star	1.58/1.58	5.1/5.9	0.70	1.01	0.45	0.82	23	Information	No	Yes	No	No
Coursera	1.5 M	1 k	0.3 M	Unkn.	2015 - 2020	Classes	1-5	1-star	0.49/0.48	72.1/72.6	1.20	1.05	0.80	0.98	12	Selling Products/Services	No	Yes	Yes	No
Jameda	0.4 M	21 k	Unkn.	Germany	2008 - 2020	Doctors	1-5	1-star	1.23/1.14	66.9/69.5	2.02	2.39	0.87	0.89	17	Information	No	No	No	Yes
Edmunds	0.7 M	0.3 M	30 k	USA	2002 - 2023	Cars	1-5	Cont.	0.90/0.83	30.7/34.3	0.95	1.09	0.51	0.92	25	Information	No	No	No	No

Table WC1: Additional information about online review datasets

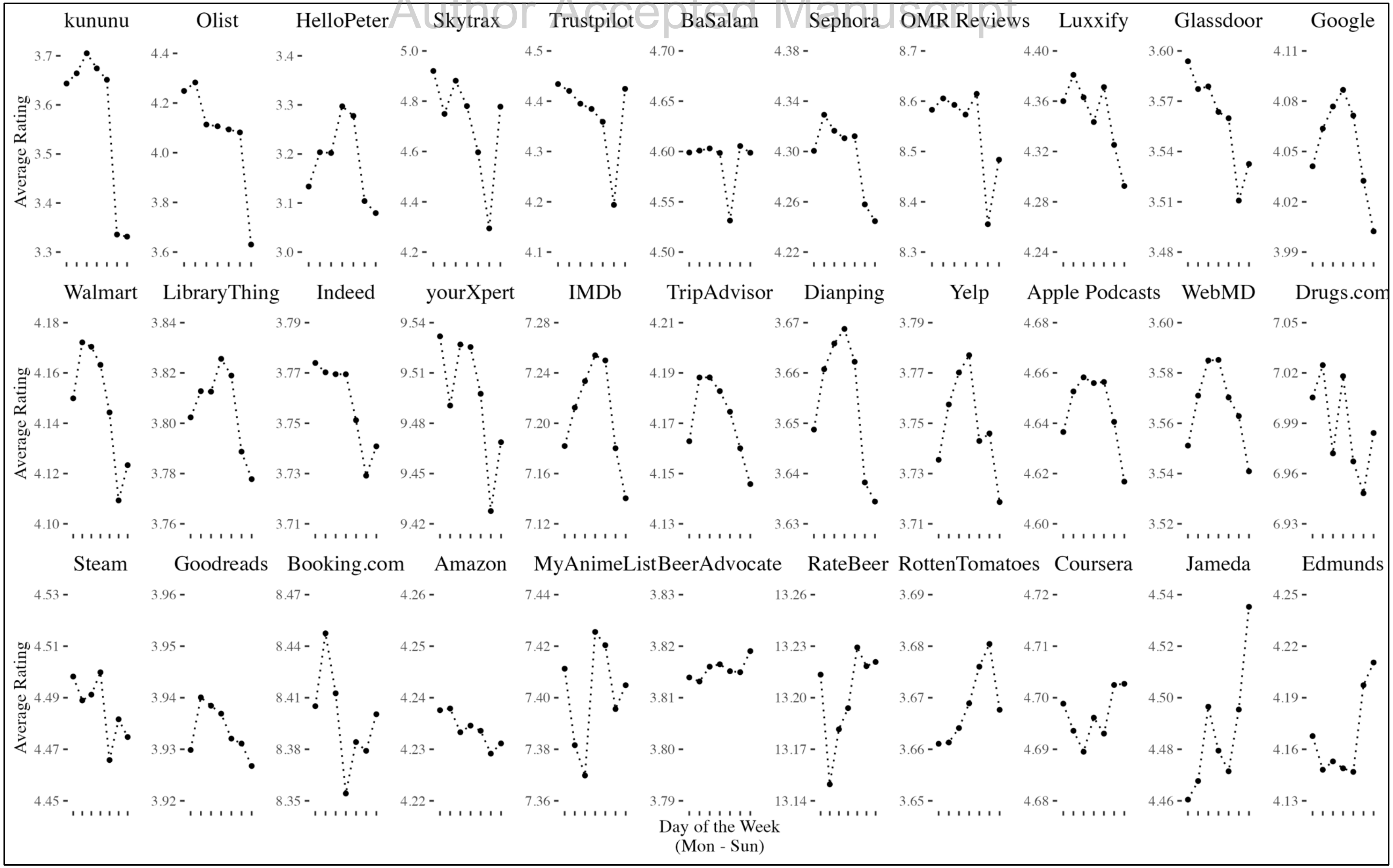
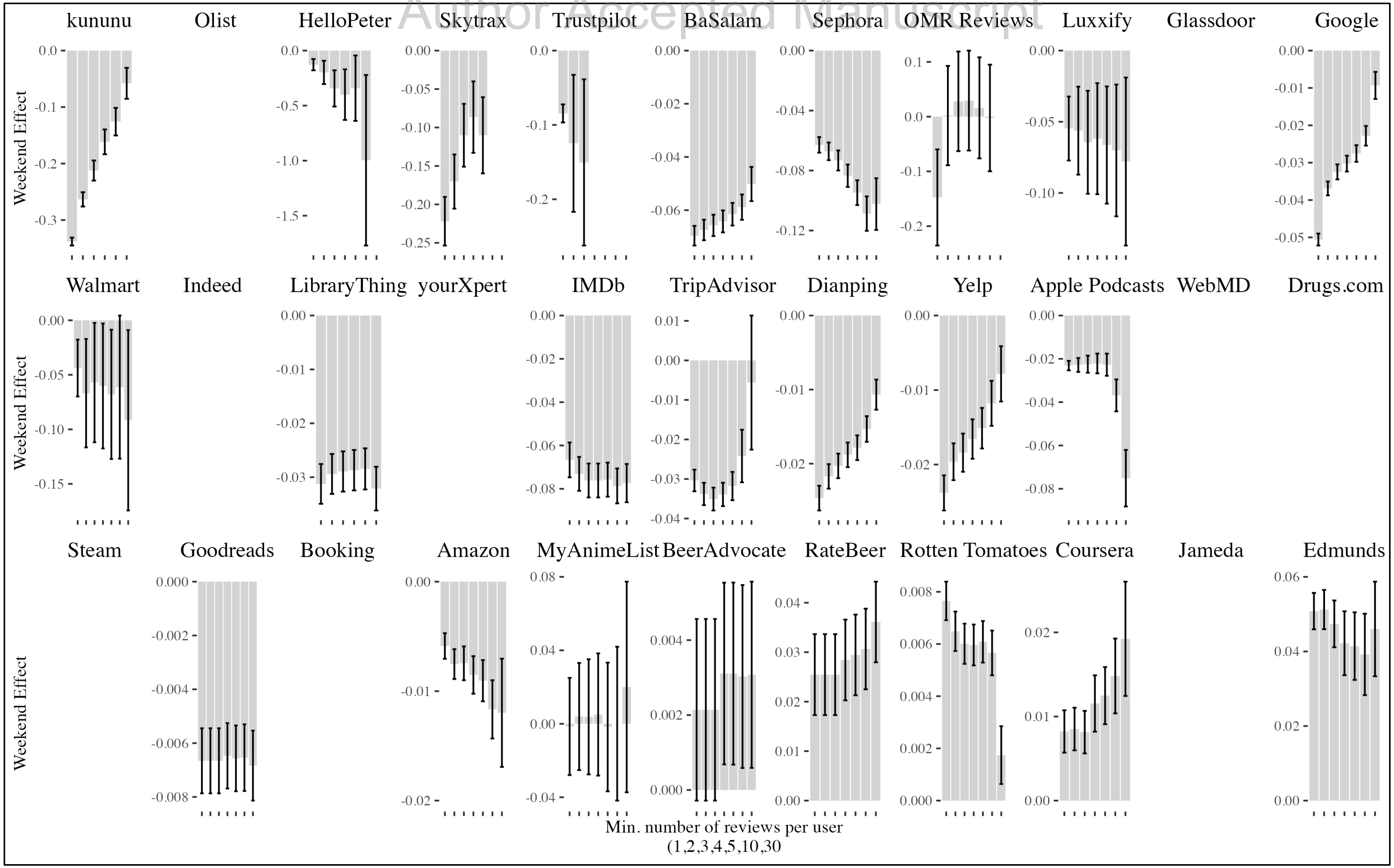
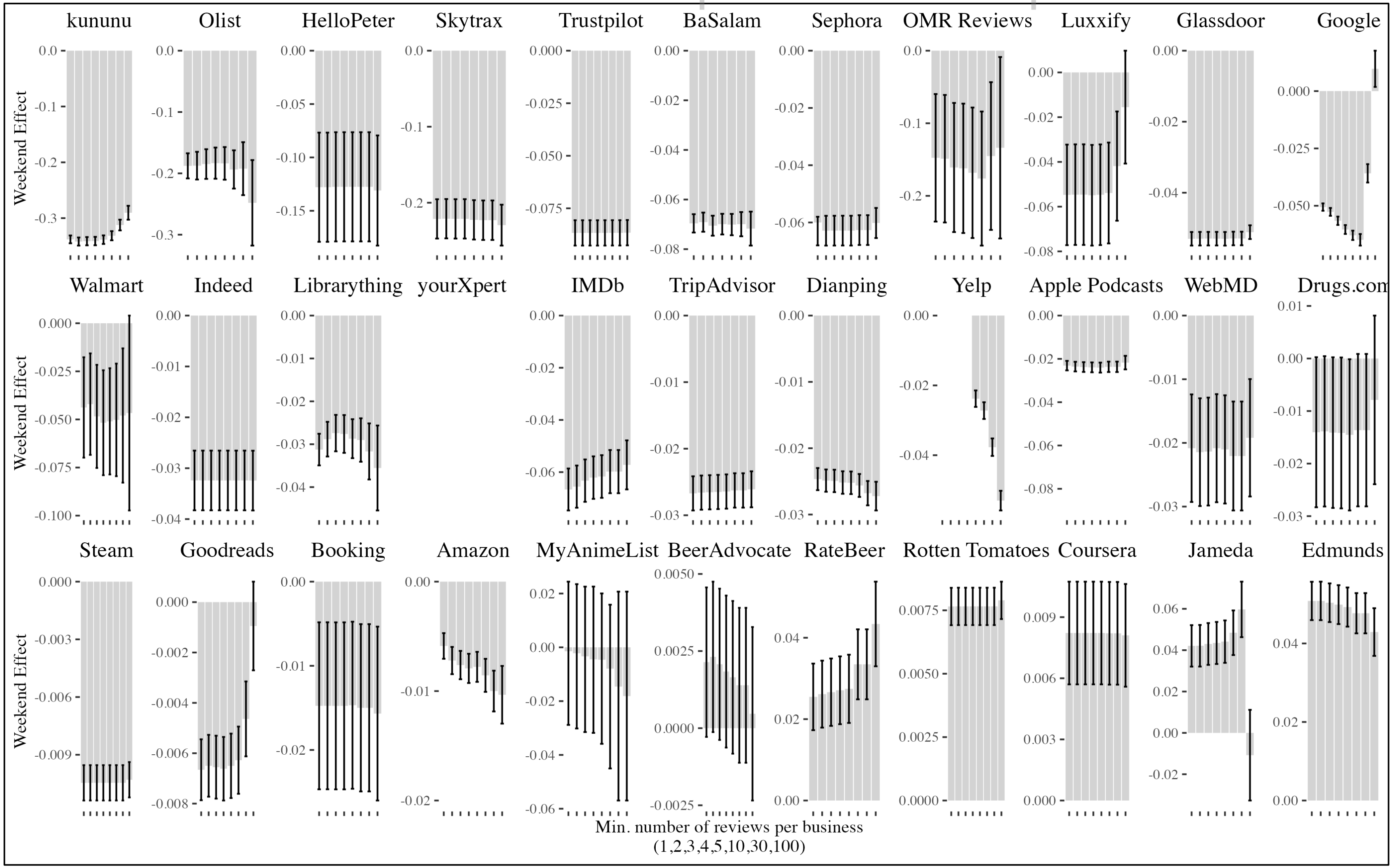


Figure WC2: Average rating by day of the week across platforms



Note: Weekend Effect = avg. weekend ratings - avg. week ratings. For Olist, Glassdoor, Indeed, yourXpert, WebMD, Drugs.com, Steam, Booking, and Jameda, our datasets have no reviewer id variable. Skytrax and Trustpilot contained a considerable amount of reviews with missing usernames. For this analysis, these reviews were excluded. Graphs are sorted by weekend effect size.

Figure WC3: The weekend effect across datasets with minimum number of reviews per user



Note: Weekend Effect = Avg. weekend ratings – avg. week ratings. For yourXpert our dataset does not have a business id variable. The dataset Yelp makes available only contains businesses with at least 5 reviews. Graphs are sorted by weekend effect size.

Figure WC4: The weekend effect across datasets with minimum number of reviews <u>per product, business or employer</u>

Platforms	Source
kununu	proprietary
Olist	https://www.kaggle.com/datasets/olistbr/brazilian-ecommerce
HelloPeter	https://www.kaggle.com/datasets/ashlingovindasamy/business-reviews-from-different-industries
Skytrax	https://www.kaggle.com/datasets/austinpeck/skytrax-reviews-dataset-august-2nd-2015;https://www.kaggle.com/datasets/efehandanisman/skytrax-airline-reviews;https://www.kaggle.com/datasets/joelljungstrom/128k-airline-reviews;https://www.kaggle.com/datasets/lokeshmadiga/airline-reviews
Trustpilot	11 different kaggle datasets we found and combined to one
BaSalam	https://www.kaggle.com/datasets/radeai/basalam-comments-and-products?select=BaSalam.products.csv
Sephora	https://www.kaggle.com/datasets/nadyinky/sephora-products-and-skincare-reviews
OMR Reviews	proprietary
Luxxify	https://www.kaggle.com/datasets/zarasarkar/makeup-insights-customer-reviews
Glassdoor	https://www.kaggle.com/datasets/davidgauthier/glassdoor-job-reviews-2; https://www.kaggle.com/datasets/davidgauthier/glassdoor-job-reviews
Google	https://cseweb.ucsd.edu/~jmcauley/datasets.html#google_local
Walmart	https://www.kaggle.com/datasets/promptcloud/walmart-product-reviews-dataset; https://www.kaggle.com/datasets/promptcloud/walmart-product-listings-data-2020
Indeed	https://github.com/dsp2109/NYDS_webscrape_indeed_company_review/tree/master; https://www.kaggle.com/datasets/bleuarmendariz/walmart-employee-reviews; https://www.kaggle.com/datasets/muhammedabdulazeem/employer-review-about-their-organization
Librarything	https://cseweb.ucsd.edu/~jmcauley/datasets.html#social_data
yourXpert	proprietary
IMDb	https://www.kaggle.com/datasets/rmisra/imdb-spoiler-dataset?select=IMDB_reviews.json; https://github.com/sidooms/MovieTweetings; https://www.kaggle.com/datasets/erwinmongui/imdb-reviews?select=reviews_spelling_errors.csv
TripAdvisor	https://www.cs.cmu.edu/~jiweil/html/hotel-review.html; https://www.kaggle.com/datasets/inigolopezrioboo/a-tripadvisor-dataset-for-nlp-tasks/data
Dianping	https://lihui.info/data/dianping/; http://yongfeng.me/dataset/
Yelp	https://www.yelp.com/dataset
Apple Podcasts	https://www.kaggle.com/datasets/thoughtvector/podcastreviews/data
WebMD	https://www.kaggle.com/datasets/rohanharode07/webmd-drug-reviews-dataset; https://www.kaggle.com/datasets/sepidehparhami/webmd-reviews-for-diabetes-drugs; https://www.kaggle.com/datasets/sepidehparhami/webmd-reviews-for-hypertension-drugs; https://www.kaggle.com/datasets/sepidehparhami/psychiatric-drug-webmd-reviews
Drugs.com	https://www.kaggle.com/datasets/rabieelkharoua/patient-ratings-identifying-best-drugs?select=Drug+Reviews+%28Drugs.com%29
Steam	https://www.kaggle.com/datasets/forgemaster/steam-reviews-dataset?select=reviews-1-115.csv; https://www.kaggle.com/datasets/harisyafie/baldurs-gate-3-steam-reviews; https://www.kaggle.com/datasets/luthfim/steam-reviews-dataset; https://www.kaggle.com/datasets/najzeko/steam-reviews-2021
Goodreads	https://cseweb.ucsd.edu/~jmcauley/datasets.html#goodreads
Bookingcom	https://www.kaggle.com/datasets/thedevastator/booking-com-hotel-reviews; https://www.kaggle.com/datasets/jiashenliu/515k-hotel-reviews-data-in-europe#Hotel_Reviews.csv
Amazon	https://cseweb.ucsd.edu/~jmcauley/datasets.html#amazon_reviews
My Anime list	https://www.kaggle.com/datasets/natlee/myanimelist-comment-dataset?select=animeReviewsOrderByTime.csv
BeerAdvocate	https://cseweb.ucsd.edu/~jmcauley/datasets.html#multi_aspect
RateBeer	https://cseweb.ucsd.edu/~jmcauley/datasets.html#multi_aspect
RottenTomatoes	https://www.kaggle.com/datasets/bwandowando/rotten-tomatoes-9800-movie-critic-and-user-reviews
Coursera	https://www.kaggle.com/datasets/imuhammad/course-reviews-on-coursera?select=Coursera_reviews.csv
Jameda	Source wishes to stay undisclosed
Edmunds	https://osf.io/6n2kt/; https://www.kaggle.com/datasets/shreemunpranav/edmunds-car-review; https://www.kaggle.com/datasets/ankkur13/edmundsconsumer-car-ratings-and-reviews

Table WC5: Source of datasets

WEB APPENDIX D - Regressions, with Fixed Effects Gradually Added

	kununu				olist				HelloPeter				Skytrax				Trustpilot			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.26***	-.08***	-.23***	-.06***	-.19***		-.18***		-.19**	-.01	-.13**	-.02	-.04***	-.06**	-.04*	-.02*	-.02	-.11**	-.02	-.04*
	(.00)	(.01)	(.00)	(.01)	(.01)		(.01)		(.06)	(.05)	(.04)	(.05)	(.01)	(.02)	(.02)	(.02)	(.03)	(.03)	(.02)	(.02)
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.63***	.44***	-.09***	-.00	.19***		-.61***		1.09***	.71***	1.26***	.79***	.42***	.89***	1.07***	.43***	.96***	.81***	1.37***	1.26***
	(.00)	(.01)	(.01)	(.00)	(.01)		(.02)		(.06)	(.05)	(.10)	(.09)	(.01)	(.03)	(.04)	(.02)	(.06)	(.13)	(.09)	(.06)
Rev. volume$_{t-1}$	.01***	.01***	-.02***	-.01	-.00		-.09***		-.04***	-.12***	-.06	-.13***	-.10***	-.14***	-.35***	-.15***	.04**	-.10	.02*	-.09
	(.00)	(.00)	(.00)	(.01)	(.01)		(.01)		(.08)	(.03)	(.07)	(.03)	(.01)	(.02)	(.03)	(.01)	(.01)	(.06)	(.01)	(.06)
Fixed Effects																				
Reviewer	x	✓	x	✓	x		x		✓	x	x	✓	x	✓	x	✓	x	✓	x	✓
Product/business	x	x	✓	✓	x		✓		x	✓	✓	✓	x	x	✓	✓	x	x	✓	✓
Observations	1.1M	0.3M	1.1M	0.3M	67 k		61 k		56k	12k	56k	12k	0.4M	0.3M	0.4M	0.3M	1.2M	9k	1.2M	9k
Adj. R^2	.14	.46	.21	0.54	.02		.11		.35	.67	.46	.68	.24	.49	.27	.51	.13	.27	.14	.32
# reviewers	1.0M	0.1M		0.1M	/		/		49k	5k		5k	0.1M	54k		54k	0.4M	2k		2k
# products	0.2M		0.1M	49k	32k		8k		68		66	64	2k		1k	1k	244		234	194

	BaSalam				Sephora				OMR Reviews				Luxxify				Glassdoor			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.07***	-.04***	-.06***	-.03***	-.04***	-.00	-.04***	-.00	-.06	.07	-.01	.04	-.03**	-.02	-.02*	-.01	-.04***		-.04***	
	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.05)	(.09)	(.05)	(.10)	(.01)	(.02)	(.01)	(.02)	(.00)		(.00)	
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.24***	.16***	-.64***	-.46***	.87***	.59***	.59***	.31***	.56***	.47***	-.21***	-.37***	.58***	.52***	-.17***	-.19***	.84***		.53***	
	(.00)	(.00)	(.00)	(.00)	(.00)	(.02)	(.03)	(.02)	(.02)	(.04)	(.04)	(.06)	(.02)	(.03)	(.03)	(.04)	(.01)		(.02)	
Rev. volume$_{t-1}$	-.02***	-.00**	-.10***	-.06***	-.01***	.02***	-.06***	-.05***	.01*	.05***	-.01	-.05	.01***	.00	-.13***	-.13***	.02***		.08***	
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.01)	(.03)	(.01)	(.01)	(.01)	(.01)	(.00)		(.00)	
Fixed Effects																				
Reviewer	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x		x	
Product/business	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x		✓	
Observations	2.7M	2.3M	2.5M	2.2M	1.1M	0.8M	1.1M	0.8M	32k	16k	32k	16 k	56k	30k	56k	30k	10.7M		10.7M	
Adj. R^2	.02	.28	.11	.35	.06	.40	.07	.41	.09	.23	.14	.29	.07	.09	.13	.16	.10		.11	
# reviewers	0.9M	0.4M		0.4M	0.5M	0.2M		0.2M	3k	3k		3k	31k	6k		6k	/		/	
# products	0.7M		0.3M	0.3M	2k		2k	2k	13k		1k	1k	1k		1k	1k	36k		25k	

	Google				Walmart				Indeed				Librarything				yourXpert			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.04***	-.01***	-.01***	-.00*	-.06***	-.04	-.06***	-.04	-.03***		-.03***		-.03***	-.00	-.02***	.00	-.07**			
	(.00)	(.00)	(.00)	(.00)	(.01)	(.03)	(.01)	(.04)	(.01)		(.01)		(.00)	(.00)	(.00)	(.00)	(.02)			
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.42***	.29***	-.51***	-.34***	.43***	.37***	-.52***	-.51***	1.01***		-.75***		.41***	.36***	-.52***	-.41***				
	(.00)	(.00)	(.00)	(.00)	(.01)	(.02)	(.02)	(.05)	(.03)		(.45)		(.00)	(.00)	(.01)	(.00)				
Rev. volume$_{t-1}$	.05***	.03***	-.01***	-.02***	.04***	.04***	-.01***	.03	.03***		-.03***		.01***	.04***	-.12***	-.11***				
	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.01)	(.03)	(.01)		(.02)		(.00)	(.00)	(.00)	(.00)				
Fixed Effects																				
Reviewer	x	✓	x	✓	x	✓	x	✓	x		x		x	✓	x	✓	x			
Product/business	x	x	✓	✓	x	x	✓	✓	X		✓		x	x	✓	✓	x			
Observations	7.4M	4.2M	6.8M	3.8M	59k	12k	49k	12k	1.0M		1.0M		1.0M	1.0M	0.9M	0.9M	29k			
Adj. R^2	.10	.31	.28	.45	.07	.12	.18	.22	.06		.06		.06	.24	.16	.33	.00			
# reviewers	4.1M	0.9M		0.9M	43k	3k		3k	/		/		65k	42k		42k	/			
# products	1.7M		1.1M	1.0M	8k		4k	3k	466		466		0.1 M		88k	88k	/			

	IMDb				TripAdvisor				Dianping				Yelp				Apple Podcasts			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.04***	-.01*	-.03***	-.00	-.04***	-.04***	-.05***	-.04***	-.02***	-.01***	-.02***	-.01***	-.05***	-.03***	-.05***	-.03***	-.01***	-.00*	-.01***	-.01***
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.85***	.73*	.13***	-.05***	.79***	.76***	.17***	.11***	.65***	.60***	-.15***	-.10***	.82***	.68***	-.08***	-.04***	.91***	.63***	.38***	.27***
	(.01)	(.01)	(.02)	(.01)	(.00)	(.00)	(.01)	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.00)	(.02)
Rev. volume$_{t-1}$	-.00	.02***	-.14***	-.13***	.02***	.01***	.04***	.02***	.02***	.01***	-.00***	-.03***	.03***	.02***	-.06***	-.06***	-.02***	-.02***	-.08***	-.07***
	(.00)	(.00)	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Fixed Effects																				
Reviewer	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓
Product/business	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓
Observations	1.2M	1M	1.2M	1M	3.5M	2.9M	3.5M	2.9M	5.2M	5M	5.1M	5M	6.8M	5.7M	6.8M	5.7M	5.0M	2.8M	4.9M	2.8M
Adj. R^2	0.20	0.40	.22	.45	.12	.15	.14	.18	.10	.26	.14	.31	.19	.34	.24	.37	.18	.41	.20	.42
# reviewers	0.2M	72k		72k	1M	0.4M		0.4M	0.5M	0.4M		0.4M	1.9M	0.8M		0.8M	3.1M	0.8M		0.8M
# products	40k		18k	18k	37k		27k	27k	0.2M		0.1M	0.1M	0.2M		0.2M	0.2M	0.3M		0.2M	0.1M

	WebMD				Drugs.com				Steam				Goodreads				Booking.com			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.02***		-.02***		-.05**		-.03*		-.00***		-.00***		-.00***	-.00***	-.00***	-.00	-.02**		-.02**	
	(.00)		(.00)		(.02)		(.02)		(.00)		(.00)		(.00)	(.00)	(.00)	(.00)	(.00)		(.00)	
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.72***		-.07***		.89***		.18***		.94***		1.01***		.62***	.51***	-.24***	-.18***	.88***		.03	
	(.01)		(.02)		(.02)		(.03)		(.05)		(.06)		(.00)	(.00)	(.00)	(.00)	(.01)		(.00)	
Rev. volume$_{t-1}$	-.01***		-.07***		-.07***		-.43***		.00***		.01***		.01***	.02***	.00***	.00	-.01***		-.00	
	(.00)		(.00)		(.01)		(.02)		(.00)		(.00)		(.00)	(.00)	(.00)	(.00)	(.00)		(.00)	
Fixed Effects																				
Reviewer	x		x		x		X		x		x		x	✓	x	✓	x		x	
Product/business	x		✓		x		✓		x		✓		x	x	✓	✓	x		✓	
Observations	0.5M		0.5M		0.2M		0.2M		38M		38M		13.0M	12.9M	12.8M	12.7M	0.5M		0.5M	
Adj. R^2	.07		.09		.12		.15		.14		.15		.10	.30	.15	.36	.13		.14	
# reviewers	/		/		/		/		/		/		0.4M	0.3M		0.3M	/			
# products	8k		5k		4k		2k		8k		8k		1.2M		0.5M	0.5M	2k		2k	

	Amazon				My Anime List				BeerAdvocate				RateBeer				Rotten Tomatoes			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	-.01***	-.01***	-.01***	-.01***	.01	.00	-.00	-.01	-.00	-.00	-.00	-.00**	-.03***	-.01*	-.04***	-.01***	.01**	.00**	.01***	.00***
	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.01)	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Controls on product/business level (time-variant)																				
Avg. rating$_{t-1}$	.41***	.30***	-.50***	-.35***	.74***	.71***	-.25***	-.20***	.81***	.82***	-.05***	-.03**	.93***	.93***	.03***	.04***	1.04***	.99***	.91***	.80***
	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.02)	(.02)	(.00)	(.01)	(.01)	(.01)	(.00)	(.00)	(.00)	(.01)	(.01)	(.01)	(.03)	(.04)
Rev. volume$_{t-1}$	.01***	.01***	-.05***	-.05***	.02	.02	-.21***	-.06***	.02***	.01***	-.03***	-.04***	.02***	-.03***	-.16***	-.16***	-.00	-.03***	-.03***	-.05***
	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)	(.01)	(.02)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Fixed Effects																				
Reviewer	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓	x	✓
Product/business	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓	x	x	✓	✓
Observations	17.9M	10.9M	17.1M	10.4M	0.1M	0.1M	0.1M	0.1M	1.5M	1.5M	1.5M	1.5M	2.8M	2.8M	2.8M	2.8M	55M	51M	55M	51M
Adj. R^2	.05	.24	.15	.31	.18	.38	.24	.45	.23	.29	.27	.33	.49	.57	.53	.60	.13	.31	.14	.32
# reviewers	10.1M	3.1M		3.1M	47k	18k		18k	33k	23k		23k	29k	20k		20k	8.8M	4.7M		4.7M
# products	2.3M		1.5M	1.4M	8k		5k	5k	66k		32k	32k	110k		71k	71k	19k		10k	10k

	Coursera				Jameda				Edmunds			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Weekend (0=no;1=yes)	.01***	.01**	.01***	.01**	.03***		.01*		.05***	.02***	.05***	.02***
	(.00)	(.00)	(.00)	(.00)	(.01)		(.00)		(.00)	(.00)	(.00)	(.00)
Controls on product/business level (time-variant)												
Avg. rating_{t-1}	.88***	.87***	.54***	.53***	-.51***		.24***		.63***	.42***	-.05	.01
	(.02)	(.02)	(.03)	(.03)	(.00)		(.01)		(.01)	(.01)	(.03)	(.02)
Rev. volume_{t-1}	.00***	.00***	.01***	.00	.02***		.02***		-.02***	-.02***	-.09***	-.09***
	(.00)	(.00)	(.00)	(.00)	(.00)		(.00)		(.00)	(.00)	(.00)	(.01)
Fixed Effects												
Reviewer	x	✓	x	✓	x		x		x	✓	x	✓
Product/business	x	x	✓	✓	x		✓		x	x	✓	✓
Observations	1.5M	1.4M	1.5M	1.4M	0.3M		0.3M		0.7M	0.6M	0.7M	0.6M
Adj. R^2	.08	.49	.08	.50	.16		.25		.07	.49	.11	.52
# reviewers	0.3M	0.3M		0.3M	/		/		0.3M	0.2M		0.2M
# products	1k		1k	1k	21k		18k		30k		19k	19k

Notes: ***$p < .001$, **$p < .01$, *$p < .05$. We logged "Review volume_{t-1}", due to its skewed distribution. Standard errors in parentheses. Errors clustered at the product or business level.

Table WD1: Regressions, with fixed effects gradually added

WEB APPENDIX E - Online review manipulation

In its publicly available dataset, Yelp claims that it contains only reviews that their internal algorithm classified as unsuspicious (Mukherjee et al. 2021). Similarly, for yourXpert, reviews cannot be written unsolicited, i.e., users can review only once they have used and paid for their services and then received an email prompting them to submit a review. This makes review fraud difficult. Still, in both datasets, there is a weekend effect. For Amazon product reviews and kununu employer reviews, there are ways to identify suspected fake reviews. The Amazon dataset has a variable specifying whether a review comes from a verified purchase (i.e., stemming from a customer who bought the product and paid the full price) or a non-verified purchase. For the employer reviews, we have access to both active and inactive reviews, with the latter never displayed online because the platform's internal algorithm deems them not trustworthy.

Within Amazon, we test the differences among the three categories that show the biggest weekend effect (i.e., software, videogames, and garden, patio & lawn). We find a significant ($p < .001$) weekend effect in both verified and unverified reviews (see Table 5), with similar results in active versus inactive employer reviews (kununu)—both show a significant weekend effect (inactive reviews: $M_{week} = 3.31$, $M_{weekend} = 2.82$; active reviews: $M_{week} = 3.70$, $M_{weekend} = 3.53$; both $p < .001$).

Thus, our findings suggest that fake reviews cannot account for the observed patterns, as the weekend effect persists even in datasets and contexts where fake reviews are minimized and accounted for.

	Software		Videogames		Garden, Patio & Lawn	
	During week	**During weekend**	**During week**	**During weekend**	**During week**	**During weekend**
Unverified reviews	3.25 stars 75% n = 110,973	3.09 stars 25% n = 37,469	3.77 stars 73% n = 447,141	3.74 stars 27% n = 161,639	3.77 stars 73% n = 314,332	3.67 stars 27% n = 116,875
Verified reviews	3.75 stars 73% n = 222,177	3.73 stars 27% n = 83,018	4.11 stars 75% n = 1,440,010	4.08 stars 25% n = 481,165	4.16 stars 74% n = 3,521,543	4.13 stars 26% n = 1,216,264

Note: These are the three categories on Amazon with the highest weekend effect, chosen for illustrative purpose. As such, the results may not generalize to all categories.

Table WE1: Weekend effect in both verified and unverified Amazon reviews

WEB APPENDIX F - Platform features

	DV: Star Rating of one review
Weekend (0=no; 1=yes)	-.05*** (.01)
Ratio of weekday to weekend	.05*** (.00)
Positive imbalance	2.57*** (.00)
Reviewer Social Network (0=no; 1=yes)	-.08*** (.00)
Recognition System (0=no; 1=yes)	-.05*** (.00)
Verified Reviews Enabled (0=no; 1=yes)	.06*** (.00)
Response to Reviews Supported (0=no; 1=yes)	.20*** (.00)
Platform Category (*Base: E-commerce/Product*)	
Employer/Job/Workplace	-.14*** (.00)
Entertainment/Media	.28*** (.00)
Spec. Professional/Service	.20*** (.00)
Travel/Restaurant/Experience	-.14*** (.01
Business Modell (*Base: Information Platform*)	
Selling Products/Services	.26*** (.00)
Transaction Fee	.26*** (.01)
Interaction Effects	
Weekend*Ratio of weekday to weekend	.01* (.00)
Weekend*Positive imbalance	.00 (.03)
Weekend*Reviewer Social Network	.06*** (.01)
Weekend*Recognition System	-.01 (.01)
Weekend*Verified Reviews Enabled	-.04*** (.01)
Weekend*Response to Reviews Supported	-.03*** (.01)
Weekend*Platform Category: Employer/Job/Workplace	-.04* (.02)
Weekend*Platform Category: Entertainment/Media	-.02** (.01)
Weekend*Platform Category: Spec. Professional/Service	.07*** (.01)
Weekend*Platform Category: Travel/Restaurant/Experience	.04** (.01)
Weekend*Business Modell: Selling Products/Services	.03** (.01)
Weekend*Business Modell: Transaction Fee	.04*** (.01)
Observations	966,834
Platforms incl.	33
Adj. R2	.12

*Notes: ***p < .001, **p < .01, *p < .05. We centered the two continuous variables "Ratio of weekday to weekend" and "Positive imbalance". Standard errors are heteroskedasticity-robust (HC1), estimated via the fixest package in R.*

Table WF1: Regression platform features

WEB APPENDIX G - Merging of Yelp Businesses with Location Data

Hypothesis/Potential explanation: The weekend effect (i.e., lower online review ratings during the weekend) might be due higher crowdedness during the weekend. Due to higher crowdedness, the service is slower, perhaps service personnel is more stressed and the overall experience is worse, because the place is packed.

Goal: For as many businesses from the Yelp datasets as possible we want to get location data (i.e., a proxy for how many people visited the business on a given day) from Safegraph data. So, for each unique *business_id* in the yelp data, we try to get a unique *placekey* from Safegraph.

Data:

- Yelpdata: 150,346 businesses (with in total 7 M online reviews).
- Safegraph Data: 12.8 M points-of-interests (POIS)

Safegraph data is available from January 2018 onward. We only work with location data until the end of February 2020, because afterwards Covid restrictions in the US came into place.

Merging:

a) Preprocessing:

- We subset the Safegraph dataset to only include locations that, according to Safegraph, are located in one of 11 states where Yelp shared reviews from. This reduced the number of POIS from initially 12.8 M to 5.1 M.
- In both datasets (Yelp and Safegraph) we cleaned the name variable by lowercasing everything and excluding numbers, special characters and spaces.

b) Actual merging:

I. We look for Safegraph POIS that **share exactly the same (1) name, (2) address and (3) postal_code** with a business in Yelp. This results in <u>69k successful merges</u>.

II. Due to inconsistencies in the address variable (e.g., Str, Street, S.) in both datasets, we merge the unsuccessful ones again this time **using these variables for the merge: (1) name, (2) latitude and (3) longitude (both rounded to three decimals,** which corresponds to roughly 100 meters). This results in <u>another 25k successful merges.</u>

III. We repeated the previous step on the so far unmatched businesses, **this time rounding latitude and longitude to two digits**. Due to different methods to get the exact location (latitude and longitude) between Yelp and Safegraph and subsequently unfortunate rounding, we might have missed some businesses. Indeed, this step results in <u>another 8k successful merges</u>.

IV. Names might vary across both datasets. Therefore, in this step, we used **fuzzy matching** (i.e., R's fuzzyjoin package) **allowing for small differences** (using conservative thresholds) **between names** in both datasets. We still require the location (i.e., either address or latitude and longitude) to be the same. This results in <u>another 9k successful merges</u>.

c) De-duplication and cleaning:

Our merging process introduced a few duplicates:

- We delete a few (less than 1k) yelp *business_ids* appearing multiple times, as well a
- a few (less than 1k) Safegraph *placekeys* appearing multiple times.

Upon visual inspection, we tweaked the thresholds for the fuzzy matching for especially short and very long names a bit and following this deleted around 1k matched businesses.

=> Finally, we were left with 72% (108,653 out of the initial 150,346) of the Yelp businesses for which we are able to match location data with a high certainty. Safegraph tracked at least one visitor for 77,452 of these locations. 72,017 (68,729) [63,834] were visited at least 30 (100) [300] times. 70,931 of these locations received at least 5 reviews during both the week and the weekend, and off these 29,280 are restaurants and 26,334 are restaurants that, according to Yelp, are open both during the week and the weekend.

Sanity checks:

- We find, on a business-level, that the number of total reviews per business is positively correlated with the number of visits according to Safegraph (i.e., sg_total_visits) (corr = +0.09; $p < .001$). This correlation stays very similar and significant in subsets with at least 30, 100, or 300 accumulated visits according to SafeGraph.
- Also, the following two correlations are significant as expected:
    - Cor(volume_weekreviews, sg_avg_weekvisits) = +0.08 ($p < .001$)
    - Cor(volume_weekendreviews, sg_avg_weekendvisits) = +0.10 ($p < .001$)

Results regarding weekend-effect:
For each business, we know how many visits it received according to Safegraph on a given day of the week. Using this we build the following two variables:

- ***sg_avg_visits_perweekday:*** The sum of all visits on a Mon, Tue, Wed, Thu, and Fri for this business divided by 5.
- ***sg_avg_visits_perweekendday:*** The sum of all visits on a Sat and Sun for this business divided by 2.
- ***sg_ratio_weekendtraffic:*** *sg_avg_visits_perweekendday / (sg_avg_visits_perweekday + sg_avg_visits_perweekendday).* If this variable is smaller (larger) than 0.5, less (more) visits take place during an average weekend day.

a) Places about equally busy:

- 0.45 < *sg_ratio_weekendtraffic* < 0.55: In these 29,119 businesses the weekend effect is 0.03 ($p < .001$)
- 0.48 < *sg_ratio_weekendtraffic* < 0.52: In these 12,824 businesses the weekend effect is 0.03 ($p < .001$)
- 0.49 < *sg_ratio_weekendtraffic* < 0.51: In these 6,494 businesses the weekend effect is 0.03 ($p < .01$)

b) Places relatively busy on weekends (i.e., *sg_ratio_weekendtraffic* > 0.5):

- We find that in 35,756 businesses that are <u>more</u> frequented during an average week<u>end</u> day than during an average week day, there is a significant weekend effect of 0.05 stars ($p < .001$). Their weekend reviews are lower.
- If *sg_ratio_weekendtraffic* is even greater 0.6, then the weekend effect increases to 0.06 stars ($p < .001$).

c) Places relatively busy during the week (i.e., *sg_ratio_weekendtraffic* < 0.5):

- We find that in 41,556 businesses that are <u>less</u> frequented during an average week<u>end</u> day than during an average week day, there is no significant weekend effect (star rating difference = 0.005; $p = .28$).
- If *sg_ratio_weekendtraffic* is smaller than 0.4, then the weekend effect even turns around and is marginally significant -0.02 stars ($p < .05$). This means their weekend reviews are higher.

All above results stay very similar and significant in subsets with at least 30, 100, or 300 accumulated visits according to SafeGraph or in subsets of businesses with at least 5 reviews during both the week and the weekend. Also a subset of restaurants that, according to Yelp, are open both during the week and the weekend show similar results as above: When around equally busy during the week and the weekend, there still is a significant weekend effect of 0.05 stars ($p < .001$), while the weekend effect slightly increases when it becomes more busy during the week, but also persists when it is relatively more busy during the week.

=> In summary, we find that for businesses that are equally busy during the week and the weekend, still there is a significant weekend effect. Thus, higher crowdedness cannot be a sole driving force of the weekend effect. Especially also because we see the weekend effect persists in datasets where the crowdedness of the place arguably cannot play a role (i.e., product and employer reviews). However, we also find that relatively highly frequented places during the weekend show a bigger weekend effect than businesses relatively highly frequented during the week.

WEB APPENDIX H - Survey among Yelp Users

Respondents: We ran a pre-registered (https://aspredicted.org/S69_97L) study with 300 participants incentivized with US$2 each and recruited via Prolific. We pre-selected participants by requiring them to come from either the USA or Canada (to mirror Yelp reviewers in our secondary data), to be fluent in English, and to have an account on Yelp, which we verified through some questions that Yelp users definitely should be able to answer.

Procedure: We aimed to explore whether within the population of users, a subset of relevant characteristics differs between the week and the weekend. For this purpose, we conducted our survey both during the week (Thursday morning; n = 150) and during the weekend (Sunday morning; n = 150). We chose these two days based on our secondary data, where these are the days with the best and worst review ratings on Yelp. We assume that users who respond to surveys related to their review behavior will show a similar self-selection, i.e., users who take our survey on a weekend have a higher likelihood to be weekend reviewers compared to users who fill out the survey during the week. While we cannot link Prolific users to their Yelp account, we asked survey participants of both the Thursday and the Sunday cohort when they are usually active on Yelp. And indeed, the group surveyed during the weekend reported to be more active during the weekend and vice versa for the week group.

Results – Week versus Weekend users: The results from the secondary data suggested differences between the two types of reviewers (weekday and weekend) in terms of various constructs related to social processes. The results in the adjacent Table show feelings of being socially disconnected, trait loneliness and state loneliness (i.e., “How lonely do you feel today?”) are higher during the weekend, while at the same time subjective happiness is reduced. We further asked both groups whether they feel that they have many more (=5) or fewer (=1) friends relative to others. For the Sunday group this value was significantly lower.

Construct	Source	Scale	Thursday Group	Sunday Group	Difference (Sun-Thu)
State loneliness	(van Roekel et al. 2018)	1-7	2.53	2.99	.43***
Trait loneliness	(Hughes et al. 2004)	1-3	1.76	1.88	.12*
Social disconnectedness	(Lee, Draper, and Lee 2001)	1-6	3.11	3.34	.23*
Extraversion	(John and Srivastava 1999)	1-5	2.80	2.87	.07
Subjective happiness	(Lyubomirsky and Lepper 1999)	1-7	4.50	4.20	-.30*
Satisfaction with life	(Diener et al. 1985)	1-5	3.03	3.00	-.03
Positive affect	(Thompson 2007)	1-5	3.44	3.42	-.02
Negative affect	(Thompson 2007)	1-5	2.00	2.23	.23***
Friends rel. to others	(Zuckerman and Jost 2001)	1-5	2.39	2.25	-.14*

Notes: *$p < .1$; **$p < .05$; ***$p < .01$. Significance was assessed with a two-sided t-test.

Table WH1: Comparing Thursday to Sunday users across a subset of characteristics

The differences we find between survey respondents that participated on a Thursday versus those that participated on a Sunday align with what we observe in secondary data: Weekend reviewers seem to be different than week reviewers. Our findings from the survey about weekend users being more socially disconnected likely stems from the same phenomenon that drives the differences in the secondary data. Namely, a temporal reviewer selection. Both online reviewers and our survey-takers who respond to a survey or write a review on the weekend represent a self-selected sample and are not representative of the whole population, because if they were our results should mirror previous findings of increased happiness during the weekend (e.g., Helliwell and Wang 2015). This is in line with Arechar, Kraft-Todd, and Rand (2017), who show that participant characteristics and behavior vary over time on platforms such as MTurk or Prolific. Similarly, we argue for online review platforms, that while in general people are happier on the weekend, those who opt to write an online review during the weekend are not.

Results – Online connections and "real" friends: In secondary data, we find that on both Yelp and Dianping weekend reviewers have significantly fewer friends on the respective platform. Past research finds that one's online social network mirrors that in the offline world

(Dunbar 2016; Dunbar et al. 2015). For example, Helliwell and Huang 2013 find that within a sample of 5,025 respondents, the size of their real-life social network positively correlates (r = 0.25) to the size of their online social network. Given that Yelp is not a typical social network platform, we use our survey to establish whether this finding also holds for online review platforms and specifically Yelp. To assess the number of friends in real-life we used definitions from (Dunbar 2021) where the *support group* is considered as the closest friends, followed by the *sympathy group* and *acquaintances* moving towards the outer layers of one's network. Since the number of Yelp friends is very skewed (many respondents with few friends and few respondents with many friends), we additionally take the log of this variable. Our approach comes with the limitation that all values are self-reported values by participants. We demonstrate that the number of connections on Yelp and the number of close friends in real-life is positively correlated, r = 0.21 ($p < .01$) (see the adjacent Table for details).

	I.	II.	III.	IV.	V.	VI.
I. Support group	1					
II. Sympathy group	.36***	1				
III. Acquaintances	.32***	.33***	1			
IV. Friends relative to others	.23***	.28***	.34***	1		
V. Number of Yelp friends	.21***	.18***	.11**	.11**	1	
VI. log10(Number of Yelp friends)	.20***	.09*	.08*	.13**	.79***	1

Note: *$p < .1$; **$p < .05$; ***$p < .01$

Table WH2: Correlation between number of Yelp friends and real-life friends

WEB APPENDIX I - Study 4: An Experiment with Prolific Users

	N	Social disconnectedness	Trait loneliness	Friend compared to others	Number of past reviews submitted	Age (in years)	Sex (% Female)	Ethnicity (% Non-white)	Country of birth (% outside USA)	Employment status (% Not full-time)
Randomly allocated to be invited to review during week	500	3.29	1.78	2.15	5.05	39.90	54.33	33.60	13.80	38.00
Randomly allocated to be invited to review during weekend	500	3.39	1.83	2.13	4.69	38.79	52.94	33.33	14.77	38.32
Difference (weekend – week)		0.10	0.05	-0.02	-0.36	-1.11	-1.39	-0.27	0.97	0.32
P-Value of two-sided t-test		.25	.30	.68	.38	.18	.66	.93	.66	.92

Notes: Social disconnectedness according to Lee, Draper, and Lee (2001), trait loneliness according to Hughes et al. (2004) and friends compared to other as in Zuckerman and Jost (2001)

Table WI1: Characteristics of participants that were randomly allocated to either review during the week or the weekend.

	N	Social disconnectedness	Trait loneliness	Friend compared to others	Number of past reviews submitted	Age (in years)	Sex (% Female)	Ethnicity (% Non-white)	Country of birth (% outside USA)	Employment status (% Not full-time)
Respondents who took part during week	380	3.24	1.77	2.14	5.46	40.74	55.67	34.47	14.21	35.79
Respondents who took part during weekend	280	3.43	1.82	2.07	4.23	40.00	57.66	32.74	14.95	36.30
Difference (weekend – week)		0.19	0.05	-0.07	-1.23	-0.74	1.99	-1.73	0.74	0.51
P-Value of two-sided t-test		.09	.39	.31	.02	.47	.61	.64	.79	.89

Notes: Social disconnectedness according to Lee, Draper, and Lee (2001), trait loneliness according to Hughes et al. (2004) and friends compared to other as in

Table WI2: Characteristics of participants that selected into taking part in the review invitation

WEB APPENDIX - References

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