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Using social media to evaluate associations between parking supply and parking sentiment

Andrew Mondschein [a,*], David A. King [b], Christopher Hoehne [b], Zhiqiu Jiang [a], Mikhail Chester [c]

[a] Department of Urban and Environmental Planning, University of Virginia School of Architecture, Charlottesville, VA 22904, United States of America
[b] Arizona State University, School of Geographical Sciences and Urban Planning, 5636 Lattie F. Coor Hall, Tempe, AZ 85287-5302, United States of America
[c] Arizona State University, School of Sustainable Engineering and the Built Environment, 660 S. College Avenue, Tempe, AZ 85281, United States of America

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ABSTRACT

A common complaint against changing parking requirements is that parking is critical for businesses to survive. Such statements are generally taken as a statement of fact by planners and local officials, yet there is little empirical work in support of this claim. This research examines how online business reviews reflect customer sentiment toward parking, and how this sentiment is associated with the supply of parking. The Phoenix, Arizona region is used for this analysis. The parking supply at the parcel level is combined with data from user-generated Yelp business reviews to assess satisfaction or frustration with parking at different types of businesses in commercial districts across the region. Results suggest that parking is mentioned in about 5% of overall reviews, and when mentioned in reviews it is most often as a negative characteristic of the establishment. Reviews that mention parking also give significantly lower ratings to businesses. The analysis shows that parking sentiment may be associated in some cases with parking supply, e.g. districts with more parking spaces per business tend to have more positive parking sentiment. Additionally, in areas with shared parking facilities, parking was generally viewed more positively or mentioned less frequently. These findings suggest that parking supply is part of a customer's overall perception of a business, though not a major component, and that shared parking facilities are not associated with negative reviews. Implications for policy are that shared parking can be part of an overall package of parking reforms that satisfy businesses and customers alike.

1. Introduction

Transportation access is a critical factor for businesses. Highly accessible sites command higher rents because of the ease with which people can get to them. Since accessibility of a business should explain some of its patronage, it follows that when customers review a business, their transportation experience getting to the establishment affect their overall sentiment of their experience. In addition, business owners and managers worry about how people will get to their stores and would like to know more about the ease or difficulty that people have getting to them. Encompassing the concerns of patrons and proprietors, transportation and land use planners seek to promote access and foster economic activity through zoning, parking requirements, and the provision of transportation infrastructure. Despite well-publicized business complaints about parking for customers, few businesses, business groups, or municipalities collect systematic data about parking sentiment. However, sentiment is a critical component of consumer behavior in cities (Sparks et al., 2013); systematic analysis of parking sentiment may reveal whether the local supply of parking, regulated by urban planners, meets the needs of local consumers and establishments. In this study, we use content from an online location-based social network, Yelp, to examine the relationship between reviewer parking sentiment and establishment parking supply for major commercial districts and corridors in the Phoenix, Arizona region. We test whether sentiment varies across districts, and whether those variations are due, in part, to the supply of parking in those districts, and whether parking sentiment is associated with overall establishment sentiment.

1.1. Background and hypothesis

Online reviews have been used to assess a range of socio-economic urban phenomena. As one example, social media can reveal associations with gentrification (Gibbons et al., 2018; Reades et al., 2019; Zukin et al., 2017). In another, using just restaurant review data from Chinese cities, MIT researchers used machine learning techniques to assess neighborhood socio-economic characteristics using online reviews (Dong et al., 2019). They found that most of the variation in local socio-economic attributes can be predicted by restaurant data. Social media is also used to extract information on travel behavior and experiences is an emerging approach to transportation research, including analyses of multimodal travel choices around transit stations (Mondschein, 2015), public transit stigma (Schweitzer, 2014), and the role of social media in trip planning (Mjahed et al., 2017). Location-based social media have been used by scholars to

* Corresponding author.
E-mail addresses: mondschein@virginia.edu, (A. Mondschein), david.a.king@asu.edu, (D.A. King), cghoehne@asu.edu, (C. Hoehne), zj3av@virginia.edu, (Z. Jiang), mchester@asu.edu. (M. Chester).

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assess the time and duration of activities, mode share, and overall urban mobility patterns (Afzalan and Sanchez, 2017; Hollander and Renski, 2017; Rashidi et al., 2017; Rybarczyk et al., 2018; Wu et al., 2014). Jiang and Mondschein (2019) use Yelp reviews to examine how far from a station people are willing to walk in a transit-adjacent commercial district. These studies utilize the logic of crowdsourcing to aggregate individual experiences into knowledge regarding local and regional travel experiences, where bits of information from many users can be aggregated to produce larger insights that can be applied generally.

In this study, rather than examine travel behavior or socio-economic factors with social media, we use Yelp reviews to examine if expressed parking sentiment, which is a measure of positive or negative feelings toward a thing or phenomenon, is associated with parking supply, which is an element of the built environment with significant implications for accessibility. The supply of parking is fundamental to site planning and regulations (Shoup, 2017). In recent years, many cities have reconsidered their required parking regulations, usually resulting in relaxing required spaces (Shoup, 2018). Such changes in the regulations are contentious, however, and often opposed by residents and businesses (King et al., 2007). Yet the evidence used to oppose reform is thin and usually reflects anecdotal viewpoints on how much parking an individual wants rather than a systematic estimate of how parking supply affects consumers' attitudes toward patronizing those businesses. We propose that the content of online reviews is one useful approach for measuring how parking sentiment is affected by parking supply. Of note, we use parking supply as a proxy for parking availability, though these are not perfect substitutes. While we do have a reasonable estimate of how many spaces exist in the study areas, we don't know to what extent they are used (meaning how many cars are parked at any location at the time of review).

Since parking is frequently touted as critical for a business' success, it follows that parking should be a criterion that customers use for evaluation. We expect that not all businesses will have the same parking demands, however. Businesses that are more discretionary, such as restaurants and entertainment as opposed to services such as legal offices, may be more affected by parking sentiment. In addition, parking supply is a product of planning as well as the distinctive economic and development histories of a location. Given those expectations, we hypothesize that a significant relationship exists between parking sentiment and parking supply, but that it will vary across locations and business types. Our analysis, at the level of major commercial districts and corridors in the Phoenix region, examines this hypothesis. We examine both how the inclusion of parking content in a review affects overall ratings for a business, and the sentiment expressed by reviewers regarding their parking experiences.

1.2. District-level analysis

We investigate the relationship between parking sentiment and parking supply at the commercial district level, comprised of centralized downtowns and linear corridors. Analysis at the district level allows for aggregating the data to a level that smooths variations associated with any one business. Seven unique districts were identified in the Phoenix region. The districts were selected for having contiguous business activity, including cultural activities and restaurant density. The districts were also selected to be representative of areas with a mix of businesses and age of buildings, and not conventional suburban shopping malls with ample parking, which are common in the region. These seven districts may not represent all potential districts for study in the region, but the intent in this research is to be more exploratory and establish whether reviewer sentiment is associated with parking supply. Overall, these districts are overrepresented in the reviews that mention parking. While they comprise 6.7% of the consumer businesses in the Phoenix Yelp database, they are the source 20.2% of the reviews that mention parking.

The districts studied are shown in Fig. 1. Three downtown districts are used: Phoenix, Tempe and Old Town Scottsdale. These are the three largest downtown areas in the region, though the region is quite polycentric so there is no dominant core. All three downtown areas offer some exceptions to accessory parking, where required parking must be on the same site as

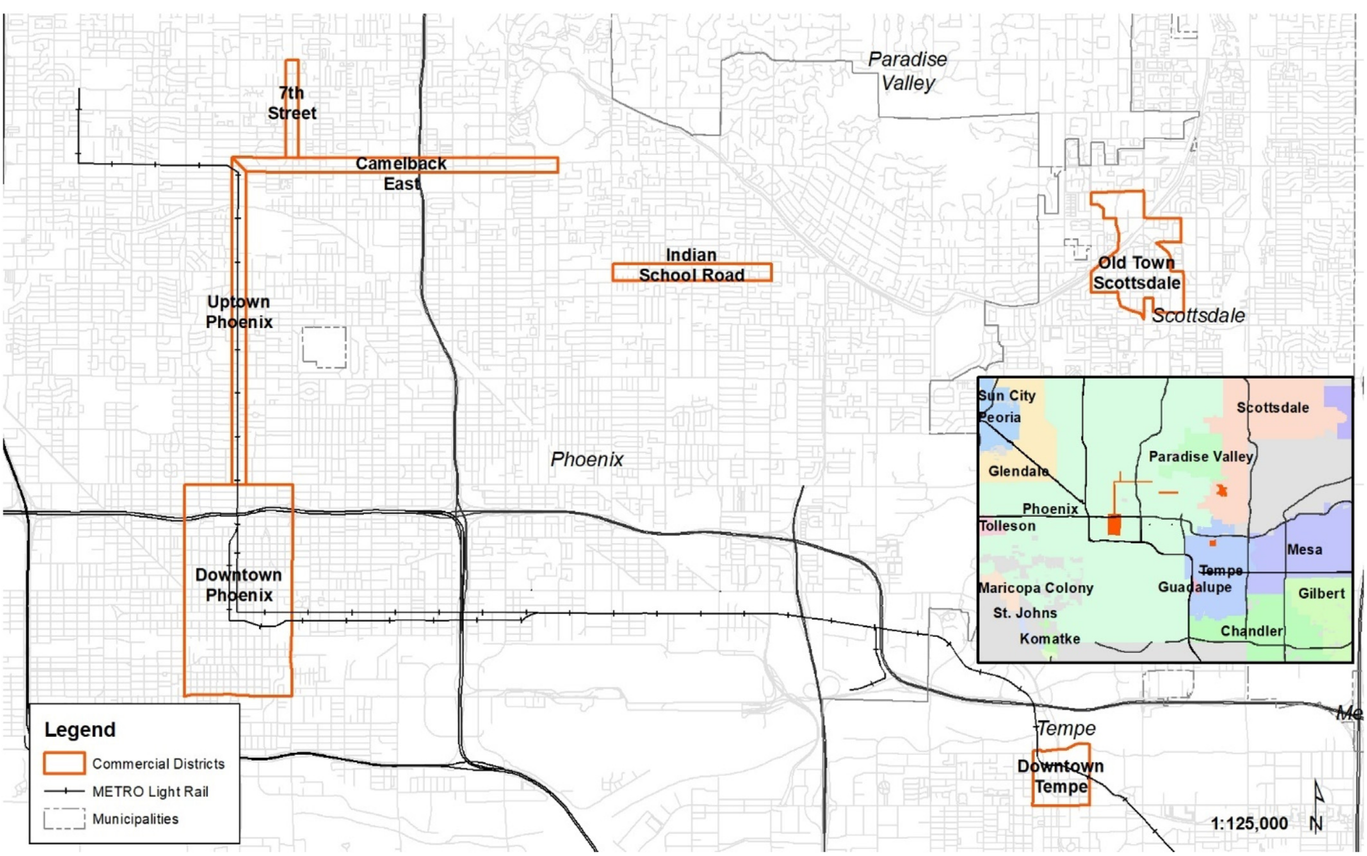


Fig. 1. Study commercial districts in the Phoenix METRO.

the business, and all three promote walkability and alternatives to driving. For instance, Scottsdale allows for waived parking, off-site parking to meet requirements and an in-lieu program where required parking can be reduced if developers supply public art. This means many places in downtowns do not have on-site parking and rely on shared parking. Residential parking permit districts are common in the areas near the downtowns and corridors studied.

Phoenix is the largest downtown and a traditional center of commercial activity due to the presence of the state capital, Phoenix city offices, other governmental activities and an Arizona State University (ASU) campus. Downtown Tempe features the main ASU campus. Both downtown Phoenix and Tempe have daytime populations of about 80,000 when the academic year is in session, though downtown Tempe currently features more housing. Downtown Phoenix has not traditionally been a center of retail and entertainment activity, though many recent additions are changing this. A convention center and professional sports arena are two large efforts to improve entertainment options that were built decades ago. More recently, mixed-use developments and apartment construction have helped increase downtown activities, and there is a thriving art scene along Roosevelt Row, which holds a monthly art crawl that attracts thousands of people.

Downtown Tempe, by contrast, is a compact area immediately next to the ASU campus. The ASU system is the largest university in the country in terms of enrollment, and the lion's share of activity happens in Tempe. This means that downtown Tempe is oriented toward college activities but also subject to the ebb and flow of the academic calendar. Businesses in the area cater more toward college students. Tempe is investing substantially in alternatives to driving, including a new streetcar under construction and expansion of their bike lane network. Downtown Tempe parking is unique in that the business improvement district, Downtown Tempe Authority, plays a large role in managing parking in the area.

Downtown Scottsdale is an entertainment center of low-slung buildings housing art galleries, restaurants and retail services, among other commercial activities. Of the three downtown areas, Scottsdale is the most entertainment oriented and has the most street parking, which is free for 3 h. Structured parking is also prevalent and is located closer to the edges of downtown. The area is served by fleets of golf cart jitneys to shuttle people to destinations within the downtown area.

The corridors included are functionally different than the downtown areas. The corridors are along major arterial roads, with at least four lanes of traffic and no street parking on the main arterials. No parking along arterials is a design choice to maximize vehicular speed and flow. As a result, these are not pedestrian friendly areas and few people walk between shops and restaurants. This is despite the corridors being retail oriented, especially with regard to restaurants. Along the study corridors are mixes of strip malls and stand-alone businesses. In strip malls, all businesses in the mall share a common parking lot (though frequently place signs reserving spaces in front of their own shops). The stand-alone businesses have parking on their sites. Many restaurants along the corridors have valet parking in the evening to maximize the number of cars they can park in their constrained lots, though this is far from universal.

2. Data and methods

Our analysis uses data on parking supply and parking sentiment, examining relationships among supply and sentiment across commercial districts in the Phoenix, Arizona region. The methods used to develop both the supply and sentiment data are summarized in this section.

2.1. Parking supply

A dataset at the parcel-level was created by cross-referencing property-use data and roadway data with minimum parking requirements in the region. Off-street parking was estimated for each parcel according to the required minimum parking by property type outlined in zoning codes. Minimum parking requirements were codified for all cities and towns in the region and applied to the 1.6 million parcels of land designated by over 2000 different property types. Total parking was calculated by using the requirement in the zoning code and the size of each building, which was retrieved from the Maricopa County Assessor's Office webpage (see Hoehne et al. (2019) for full details and results). As most arterial roads in the region do not have on-street parking, and the districts included have or are adjacent to residential parking permit districts, on-street parking is not included in the parking supply analyzed here. The estimated parking spaces were validated by manually counting spaces using satellite images, and in some cases, researchers visited sites to count the number of spaces in person. The parking inventory found that parking density is highest within downtown districts. Downtown Scottsdale has the highest density of parking (127 spaces per hectare) compared to Downtown Tempe (113) and Downtown City of Phoenix (112).

In this analysis, we aggregate parking supply data for individual parcels to the district level using two approaches, comparing their results in subsequent analysis. The first method sums the amount of parking available in all commercial parcels within our districts. The second method sum parking only for parcels within 100 m of an active business on Yelp. Not all parcels zoned as commercial have active, consumer-facing businesses for which parking would be an issue. We select a 100 m buffer as a reasonable distance that a person might walk between a business and parking. While many businesses state that they restrict parking to their own customers, in practice, some public districts and private shopping centers explicitly offer shared parking and even single-site parking is often unclearly labelled and monitored in auto-oriented commercial districts. We executed the same 100 buffer procedure for parking around restaurants and nightlife, as well as all other businesses on Yelp. In summary, for each district, we develop four measures of parking supply:

1. All commercial parcels in the district
2. Within 100 m of all active businesses in the Yelp database
3. Within 100 m of all restaurant/nightlife businesses in the Yelp database
4. Within 100 m of all other businesses in the Yelp database.

2.2. Parking sentiment

In analytic terms, sentiment is a measure of how a person feels about an experience and can be relatively more positive or negative. In this analysis, we examine parking sentiment in two ways: (1) the differences in average business ratings (Yelp stars), by district, for reviews with and without parking content, and (2) sentiment scores derived from textual comments on parking experiences in reviews on Yelp location-based social network. The first approach does not directly measure parking sentiment but uses the differences in average stars (between 1 and 5) given in reviews with parking content versus average stars in all reviews. We use *t*-tests to assess the statistical significance of those differences for each district. The second approach, utilizing natural language processing, uses a methodology implemented in the R statistical programming language (R Core Development Team, 2011). Details of the sentiment analysis methodology are reported in Jiang and Mondschein (2019). A summary of those steps includes:

1. *Identify all reviews in the Yelp dataset containing parking keywords*
   Yelp reviews for the Phoenix region were obtained from the Yelp Academic Dataset (Yelp, 2018a). These reviews total >1.6 million. Each review is associated with a business assigned a classification (e.g. "restaurant," "shopping," "service") and precise location in latitude and longitude. In the Phoenix region, 44,969 reviews contain the keywords "parking" or "parked," 2.8% of all reviews. Those reviews are distributed across 11,281 businesses (mean of parking-related reviews per business: 4, median: 2, min: 1, max: 298).
2. *Tokenize the reviews*
   In the process of sentiment analysis, first, we tokenize each parking review into three types of tokens - paragraphs, sentences and smaller word chunks. Each token must contain at least one parking keyword. Paragraph is determined by a new line in the review, sentence is determined by the ending sentence punctuation, and a word chunk is determined by punctuation in the middle of a sentence, such as a

comma. The purpose of doing so is to compare and determine the best tokenization strategy and further decide our bag of words in the next step. We clean the data for each tokenized string of text, by using the 'tm' package in the R statistical programming language. We find that the word chunk is the most appropriate representation of parking experiences. Specifically, if we used sentences as the unit of parking sentiment analysis, it may introduce error from unrelated text: Sentences with parking terms may be very long because some people use multiple commas instead of periods. Therefore, we cut down a sentence into word chunks, phrases divided by commas, and thereby isolate the phrase that actually describes parking experience for the sentiment analysis.

3. *Select dictionaries and format for the parking phrases*
Through data exploration, we selected four dictionaries with positive and negative labelled words and phrases: Harvard-IV, Loughran-McDonald, General Inquirer, and QDAP. These dictionaries each capture sentiment through different sets of words associated with quantified sentiments. The Harvard-IV and QDAP dictionaries are general purpose discourse dictionaries while Loughran-McDonald and the General Inquirer were developed for financial transactions (Saxena et al., 2018).
4. *Sentiment analysis*
We use the analyzeSentiment() function in the SentimentAnalysis package in R to generate our initial sentiment scores (Feuerriegel and Proellochs, 2019). AnalyzeSentiment() is a lexicon-based approach to classify the sentiment, returning the sentiment scores for each selected dictionary. Lexicon-based approaches to sentiment analysis use pre-existing dictionaries to estimate sentiment for texts. They differ from machine learning-based approaches, which require the analyst to supply their own labelled data prior to engaging in the sentiment analysis (Jurek et al., 2015). Using this approach, we estimate sentiment scores for our parking reviews. The initial scores range from -1 to $+1$ with -1 representing an extremely negative sentiment and $+1$ being most positive, with 0 representing a "neutral" parking experience. Table 1 includes eight randomly selected phrases their resultant sentiment scores based on the Harvard-IV dictionary, in order to provide a sense of how the analysis associates text with quantified sentiment. Note that while the positive and negative scores are generally appropriate to the text phrases, the precise values may not always reflect the intensity of sentiment that a human reviewer would interpret from the phrases.
5. *Evaluating the results*
In order to determine whether the sentiment analysis provided reasonable results, we conducted a manual assessment of 500 randomly selected scores, comparing the score assigned by the analysis to a rating (positive vs. nonpositive) assigned by a research team member. We found that the analysis is 80% accurate, with 15% of non-positive sentiments erroneously classified at positive, and 5% of positive sentiments erroneously classified as non-positive. The error, therefore, is distributed across positive and negative reviews, with some bias toward overprediction of positive reviews. We observed no spatial clustering in the error of the reviews. In addition, we assessed the correlation between parking sentiment and sentiment associated with the term "food" in a random sample of 1000 reviews and found nearly no correlation ($r = 0.04$) between parking and food sentiment within each review. This result suggests that the sentiment analysis is capable of effectively separately out sentiments for specific experiences from a set of multiple experiences within review.
The analysis should be understood given the potential demographic bias of the Yelp dataset. Yelp users have been found to be younger and more educated than the population as a whole, though race and ethnicity similar to the population (Yelp, 2018b). The demographics of Yelpers may bias the locations of reviews and sentiments expressed about parking, relative to the population as a whole. The level of accuracy and potential for bias should be kept in mind during interpretation of the results.
6. *Score factorization*
Each dictionary supplies a discrete sentiment score for each parking review. However, none of the dictionaries were developed specifically for estimating sentiment in online reviews. Instead, they were developed for a variety of purposes including general discourse and discourse about financial transactions (Saxena et al., 2018). We expect that online reviews of commercial activities may take on characteristics of general discourse as well as financial transactions (e.g. the cost of parking). Therefore, we use factor analysis to combine the variability across the four scores into a set of factors. The first factor explained almost all of the variability in the sentiment scores, and itself is highly correlated with the four original scores. The factorized score is standardized and normally distributed. We use this factorized score in the remainder of the analysis.

Table 1
Randomly selected phrases and sentiment scores.

Phrase	Sentiment score
"Limited parking…"	−0.67
"The parking here a disaster…"	−0.25
"… it was pricey and parking was challenging."	−0.17
"…they have fantastic parking in their strip mall"	0.14
"Finding parking without valet was a bit challenging …"	0.20
"The parking lot has plenty of (free) parking."	0.29
"I did enjoy the free ice though and the plentiful amount of parking in the back!"	0.31
"…street parking is free."	0.33

Table 2 shows that average sentiment scores, by district, are fairly close to zero for most districts. However, negative sentiments are more frequent than positive sentiments across all districts, with more substantial variability in the ratio of positive/negative scores, which ranges from 0.665 on Indian School Road to 0.912 in Downtown Tempe.

3. Results

We analyze the relationship between parking supply and sentiment at the level of commercial district. We ask whether parking supply has an evident relationship with how individuals feel about their parking experiences, measured in terms of parking sentiment. First, we present parking supply information organized by corridor, then examine sentiment data and examine the relationship supply and sentiment.

3.1. Parking supply by district

Table 3 describes commercial activity, parking supply, and parking supply rates for the seven districts in the Phoenix metropolitan area. Districts are sorted from largest to smallest amount of commercial square footage. Commercial activities in a district can be measured in multiple ways, and in Table 3 we present total commercial square footage, number of consumer-facing businesses, number of restaurants and nightlife establishments, and number of other businesses (non-restaurant/nightlife). Square footage and parcel count are derived from property data and the business counts are derived from Yelp, including all consumer-facing businesses located within the districts, whether or not they have been reviewed. Restaurant and nightlife businesses, as well as other businesses are subsets of all Yelp businesses.

Table 3 also shows the total number of off-street spaces in the districts using the four measures described in the Data and Methods section. Notably, the number of spaces within 100 m of all consumer businesses is generally lower than the total number of spaces in all commercial parcels, other than along the Camelback East corridor. The equivalence of the two measures for Camelback East suggests that this corridor is nearly exclusively consumer-facing, rather than hosting a mix of retail and office activities less likely to be in the Yelp dataset. Conversely, the ratio of consumer-oriented parking relative to all commercial parking is relatively low in the "downtowns" of Phoenix, Tempe, and Old Town Scottsdale. Not all parking ascribed to a district is likely to be usable by consumers,

Table 2
Average sentiment scores and positive/negative counts by district.

District name	Reviews with "parking"	Average sentiment score	Negative reviews	Positive reviews	Ratio of positive/negative reviews
Downtown Phoenix	3633	0.014	1956	1677	0.857
Old Town Scottsdale	1955	0.078	1024	931	0.909
Camelback East	1106	−0.063	619	487	0.787
Downtown Tempe	874	−0.001	457	417	0.912
Uptown Phoenix	626	0.047	331	295	0.891
Indian School Road	541	−0.106	325	216	0.665
7th Street	366	−0.035	200	166	0.830

Table 3
Commercial activity and parking supply in study districts.

	District name	Downtown Phoenix	Old Town Scottsdale	Camelback East	Downtown Tempe	Uptown Phoenix	Indian School Road	7th Street
Commercial activity	Commercial square footage (source)	28,046,379	11,621,580	5,325,880	5,152,451	4,898,613	1,560,054	789,244
	# of consumer businesses	1114	1194	363	294	185	219	86
	# of restaurants and nightlife bus.	431	401	122	176	72	88	31
	# of other businesses	683	793	241	118	113	131	55
Total parking supply	Commercial off-street spaces	41,863	22,772	12,786	9534	11,523	3349	2635
	Spaces within 100 m of consumer businesses	18,730	14,614	12,786	3889	6134	2343	1755
	Spaces within 100 m of restaurants and nightlife	8468	8475	2359	2169	1764	700	709
	Spaces within 100 m of other businesses	15,636	12,779	12,675	3206	5189	2082	1443
Parking supply rates	Spaces per 1000 ft^2 commercial	1.5	2.0	2.4	1.9	2.4	2.1	3.3
	Spaces per consumer business	16.8	12.2	35.2	13.2	33.2	10.7	20.4
	Spaces per restaurant or nightlife	19.6	21.1	19.3	12.3	24.5	8.0	22.9
	Spaces per other business	22.9	16.1	52.6	27.2	45.9	15.9	26.2

which could result is a disconnect between planners' sense of parking supply and those seeking to eat or shop in the area.

Finally, Table 3 shows the number of spaces normalized by our four measures of commercial activity. Across all commercial square footage, we find a range of 1.5 to 3.3 spaces per 1000 square feet of commercial activity, with the least number of spaces in Downtown Phoenix and the most along the smallest corridor, 7th Street. Measures of the number of spaces (with 100 m) per business – all businesses, restaurants/nightlife, or other businesses – vary considerably across business type and district. The measure varies from a low of eight spaces per restaurant on East Indian School Road to 52 spaces per "other" business on Camelback East.

3.2. Effect of parking on overall business ratings

Table 4 describes how mentions of parking in reviews are associated with differences in business ratings. Reviews mentioning parking, whether for all businesses or restaurants and nightlife only, range from 2.6% to 6.1% of all reviews. These rates of parking content in reviews are generally higher than for Phoenix reviews overall, at 2.8%. Mentioning parking at all in a review, whether positive or negative in sentiment, may be an indicator that parking is a concern in the area (Mondschein, 2015). However, whether including parking content in a review is associated with a poorer impression of the overall customer experience has not be evaluated before, to our knowledge. The table shows that for all but one district, reviews

Table 4
Parking mentions and star ratings.

	District name	Downtown Phoenix	Old Town Scottsdale	Camelback East	Downtown Tempe	Uptown Phoenix	Indian School Road	7th Street
All businesses	All reviews	61,314	74,162	26,642	21,467	14,632	14,592	7126
	Reviews mentioning parking	3633	1955	1106	874	626	541	366
	% parking reviews	5.9%	2.6%	4.2%	4.1%	4.3%	3.7%	5.1%
	Average stars	3.82	3.87	3.81	3.62	4.02	3.98	3.97
	Average stars w/ parking	3.67	3.80	3.73	3.64	3.85	3.73	3.47
	Difference	−0.15	−0.07	−0.08	0.02	−0.17	−0.26	−0.50
	t-Test significance (p value)	**0.0001**	**0.0329**	**0.0776**	0.6778	**0.0005**	**0.0001**	**0.0001**
Restaurants/nightlife	All reviews	47,125	58,899	18,880	18,730	12,291	11,879	5637
	Reviews mentioning parking	2266	1410	904	654	525	488	342
	% parking reviews	4.8%	2.4%	4.8%	3.5%	4.3%	4.1%	6.1%
	Average stars	3.81	3.78	3.86	3.60	4.00	3.93	3.88
	Average stars w/ parking	3.76	3.77	3.84	3.62	3.91	3.73	3.44
	Difference	−0.05	−0.01	−0.02	0.02	−0.10	−0.20	−0.44
	t-Test significance (p value)	**0.0554**	0.3974	0.6247	0.6939	**0.0715**	**0.0006**	**0.0001**
Other businesses	All reviews	14,189	15,263	7762	2737	2341	2713	1489
	Reviews mentioning parking	1367	545	202	220	101	53	25
	% parking reviews	9.6%	3.6%	2.6%	8.0%	4.3%	2.0%	1.7%
	Average stars	3.87	4.13	3.67	3.74	4.12	4.20	4.32
	Average stars w/ parking	3.53	3.89	3.23	3.69	3.54	3.68	4.04
	Difference	−0.34	−0.25	−0.44	−0.05	−0.58	−0.52	−0.28
	t-Test significance (p value)	**0.0001**	**0.0001**	**0.0003**	0.6258	**0.0001**	**0.0079**	0.3103

mentioning parking are have significantly lower star ratings than star ratings overall for the district. In all but Downtown Tempe, mentioning parking at all is associated with anywhere from a −0.08 to −0.50 star deduction. For downtown Tempe, the negligible effects are likely the result of the areas shared parking. For a 1- to 5-star scale, this difference is substantial, and *t*-tests of the difference indicate that all of rating deficits are statistically significant. Note that significant p-values ($p < 0.10$) are shown in **bold**.

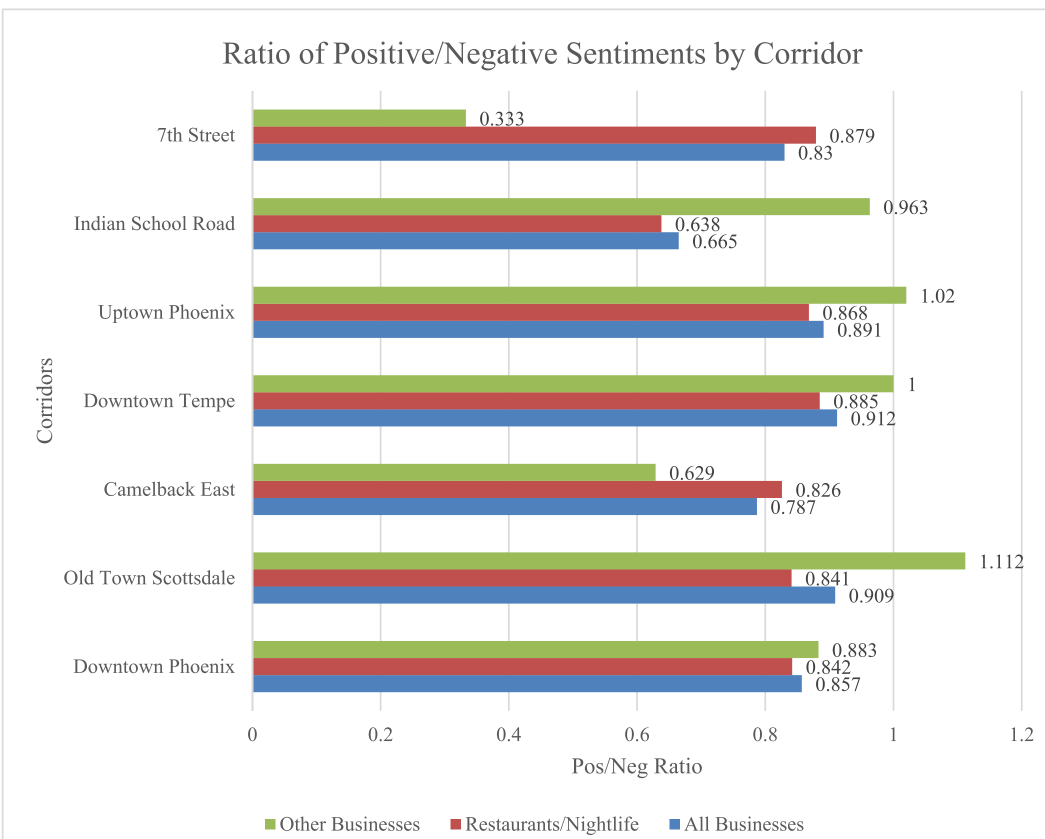
Star rating deficits in reviews mentioning parking appear to be generally larger and more statistically significant for "other" businesses rather than restaurants/nightlife. This contradicts our expectation that restaurants and nightlife would be more likely to face competitive pressures where a parking issue would reduce the reviewer's overall experience rating. It is also possible that reviewers are more likely to expect parking challenges at restaurants and nightlife and less likely to "count off" for anticipated difficulties. Some districts exhibit particularly large rating deficits when parking is mentioned regardless of business type, particularly the smaller neighborhood corridors such as Indian School Road and 7th Street. Still, star ratings do not directly measure sentiment toward the parking experience itself, which we address in the next section.

3.3. Co-evaluating parking sentiment and parking supply

Using natural language processing, we evaluate and score the sentiment of each review that mentions parking. Specifically, we evaluate the sentiment of the text concerning parking, within the larger review. We classify each review as either positive or negative based on its score, and then calculate the ratio of positive to negative reviews within each district, for all consumer businesses, restaurants/nightlife, and other (non-restaurant/nightlife) businesses. The results are presented in Fig. 2. As described in the Data and Methods section, the sentiment analysis has a slight positive bias, so we expect that average parking sentiment should be somewhat worse for all corridors. However, because we are most interested in relative comparisons across corridors rather than the absolute number of positive or negative reviews, this bias should not have a substantial effect on the results.

Negative reviews dominate in all districts despite the positive bias in the sentiment analysis. Parking reviews for restaurants and nightlife establishments are consistently negative, while "other" businesses have relatively positive parking sentiment ratios, except for the major outlier of 7th Street. Downtown Tempe and Old Town Scottsdale have the most relatively positive reviews across business categories. By contrast, Indian School Road has particularly negative reviews for all businesses and restaurants/nightlife, with ratios of 0.665 and 0.638, respectively. In general, the commercial corridors have more negative parking sentiment than the downtowns, with parking sentiment in Uptown Phoenix more like a downtown despite its linearity.

How does parking sentiment compare with parking supply? Fig. 2 also reports on the correlation between the positive/negative sentiment ratios and two measures of parking supply. Please note, we utilize correlation here descriptively, simply to assess the nature of the relationship between variables measuring parking supply and sentiment. Seeking statistical



Correlations between Parking Supply and Pos/Neg Sentiment Ratio	*All Businesses*	**Restaurants/Nightlife**	**Other Businesses**
Parking per Sq ft in All Commercial Parcels	0.45	0.54	0.00
Parking per Business within 100m of Business, by Type	0.07	0.70	-0.26

Fig. 2. Positive/negative sentiment ratios and correlations with parking supply.

significance would not be appropriate for a sample size of seven commercial districts. The parking supply data is taken from Table 3. In the first row of correlations, we present the relationship between parking sentiment and the parking per square foot for all commercial parcels in our districts. This measure of parking supply does not vary by business type. We observe a positive relationship across categories, so that as parking supply increases, positive sentiment increase. This positive relationship is near zero, however for the "other businesses" category. In the second row of correlations, we examine the more spatially refined measure of supply: parking supply per business within 100 m of businesses. These supply measures vary by business type. In this case, we observe a strong positive correlation between parking supply and sentiment for restaurants/nightlife, with little evident relationship for other (non-restaurant/nightlife) businesses. While these measures cannot be evaluated with statistical significance, they suggest that more ample parking supplies, at least for restaurants and nightlife, may be associated with positive sentiments toward parking.

4. Discussion

The results suggest that the supply and quality of parking is considered when customers review businesses. This relationship is moderate at best, however, and not likely the determining factor of overall satisfaction with a business. Yet when parking is mentioned in reviews, it usually is negatively described. Surprisingly, the effect was somewhat stronger for non-restaurant businesses. We had hypothesized that restaurants are more sensitive to parking woes as demand for restaurants can be more elastic as people have many choices about where they can go. Still, the difference in Yelp star ratings was significant for restaurants in multiple districts. Even small differences in star ratings can affect the popularity of a business (Luca, 2016), so it is likely that business owners have reason for concern if reviewers feel the need to comment on parking when describing their overall experience. We also examined the relationship of Yelp stars (overall business ratings) to parking sentiment, and found a weak-moderate positive correlation, $r = 0.158$, between Yelp stars and positive parking sentiment, for all parking reviews in Phoenix. This result reinforces our finding in Table 4 that parking experiences have some effect on overall ratings but are not the only factor. Coupled with our observation that sentiments for different parts of a review are generally uncorrelated (e.g. "parking" vs. "food"), we propose a conceptualization of Yelp reviews as a series of experiences, each with its own sentiment that contribute to an overall experience with an overall rating (Yelp stars).

Districts with shared parking facilities scored modestly higher on reviewer parking sentiment compared to the corridors. Shared parking in the downtown areas isn't usually free, but structured parking is ample. For instance, in downtown Phoenix and Tempe, off-street parking is paid, while in Scottsdale all parking up to 3 h is free. One reason the availability of shared parking may be associated with more positive sentiment is that individual businesses will not be associated with parking supply. We don't know if reviewers are less happy with their parking experience in shared parking areas, but we do show that if they are less happy, it is not reflected on the businesses they frequent. We suggest that research regarding consumer sentiment about shared parking is warranted.

Overall, there are three main findings of interest. First, while we don't find a strong association between parking sentiment and business sentiment, we do find some association. Being that opposition to parking reform often comes from businesses concerned that parking woes will harm their business, this analysis suggests that such concern may be overblown. That said, the second finding is that corridor-level shared parking is associated with more positive sentiment. This suggests that shared parking may separate customer complaints about parking from their attitudes toward businesses. From a policy perspective, promotion of shared parking over accessory parking (that which is required to be on site) can not only reduce business complaints about parking that may lower online reviews, but can improve a district's access by transit, walking and other modes (Mukhija and Shoup, 2006; Willson, 2005). Lastly, this exploratory research does show that the relationships between parking supply and business sentiment vary across business types and neighborhood or corridor characteristics. Future research should explore shared parking more in depth, but also how parking supply affects overall demand for a businesses and alternative means of travel. For instance, if the data were available scholars could test if parking supply was associated with the use of Uber or Lyft, where we might expect places with constrained supply realizing higher rates of ride hailing trips.

5. Conclusions

This research presents an analysis of reviewer sentiment about parking with parking supply and overall sentiment of businesses in the Phoenix region. We find that parking is of interest to Yelp reviewers, which can be used to gauge sentiment about parking in commercial districts and corridors. The analysis shows a relationship between negative parking sentiment and supply of available parking, but this is a weak relationship in most places, except for the places with the least amount of parking per business. We do show that star ratings for businesses are lower when parking is included in the review. This lends credence to business concerns about parking supply affecting customers. There is substantial geographic variation to these sentiments, however, so the overall mix of transport options and activities nearby should be accounted for when assessing how businesses are affected by parking. In downtown districts, parking sentiment improves.

We caution that these results should not be interpreted that fewer available parking spaces results in poor business performance. Such a relationship is not shown and is extremely difficult to study with any precision. The associations among supply, sentiment, and actual business activity would be a clear next step for this research. Certainly, customers need to access businesses, and in auto-oriented places such as metropolitan Phoenix, most customers are going to drive or be driven. Yet for policy, one takeaway is that shared parking is not associated with poorer online reviews. Parking sentiment was slightly higher in places with shared parking. This suggests, speculatively, that shared parking may be one way to assuage business concerns about losing accessory parking while maintaining customer satisfaction.

This study is presented as an exploratory analysis to assess whether online business reviews, in this case Yelp data, are of use to planners and policymakers to better understand how parking is associated with customer sentiment. The results are clear that there are relationships, but most of the effects are small as measured. However, the small effect sizes mask substantial variation across business types and neighborhood characteristics, and these differences deserve further research. Transportation access, which for many businesses includes parking, are an important policy area that can be better informed through the use of user-generated business reviews.

CRedIT author statement

Andrew Mondschein: Conceptualization, Methodology, Formal analysis, Writing – original draft, review & editing, Visualization

David A. King: Conceptualization, Methodology, Formal analysis, Writing – original draft, review & editing

Christopher Hoehne: Methodology, Validation, Data curation

Zhiqiu Jiang: Methodology, Validation, Data curation, Writing – review & editing

Mikhail Chester: Methodology, Validation, Data curation.

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Update

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Erratum

Erratum regarding missing Declaration of Competing Interest statements in previously published articles

A **Declaration of Competing Interest** statements were not included in the published version of the following articles that appeared in previous issues of Transportation Research Interdisciplinary Perspectives. The appropriate Declaration/Competing Interest statements, provided by the Authors, are included below.

1. "The challenges impeding traffic safety improvements in the Kurdistan Region of Iraq" [Transportation Research Interdisciplinary Perspectives, 2019; 2: 100029] https://doi.org/10.1016/j.trip.2019.100029
2. "Facilitating practices for sustainable car sharing policies – An integrated approach utilizing user data, urban form variables and mobility patterns" [Transportation Research Interdisciplinary Perspectives, 2019; 2: 100055] https://doi.org/10.1016/j.trip.2019.100055
3. "Factors associated with physical, psychological and functional outcomes in adult trauma patients following Road Traffic Crash: A scoping literature review" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100061] https://doi.org/10.1016/j.trip.2019.100061
4. "Computing optimum traffic signal cycle length considering vehicle delay and fuel consumption" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100021] https://doi.org/10.1016/j.trip.2019.100021
5. "Link-level travel time measures-based level of service thresholds by the posted speed limit" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100068] https://doi.org/10.1016/j.trip.2019.100068
6. "Using the abstraction hierarchy to identify how the purpose and structure of road transport systems contributes to road trauma" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100067] https://doi.org/10.1016/j.trip.2019.100067
7. "Factors influencing Pedestrian Speed in Level of Service (LOS) of pedestrian facilities" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100066] https://doi.org/10.1016/j.trip.2019.100066
8. "Embedding aircraft system modeling to ATM safety assessment techniques" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100026] https://doi.org/10.1016/j.trip.2019.100026
9. "The impact on neighbourhood residential property valuations of a newly proposed public transport project: The Sydney Northwest Metro case study" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100070] https://doi.org/10.1016/j.trip.2019.100070
10. "Creating a prediction model of passenger preference between low cost and legacy airlines" [Transportation Research Interdisciplinary Perspectives, 2019; 3: 100075] https://doi.org/10.1016/j.trip.2019.100075
11. "Using social media to evaluate associations between parking supply and parking sentiment" [Transportation Research Interdisciplinary Perspectives, 2020; 4: 100085] https://doi.org/10.1016/j.trip.2019.100085
12. "Emerging data for pedestrian and bicycle monitoring: Sources and applications" [Transportation Research Interdisciplinary Perspectives, 2020; 4: 100095] https://doi.org/10.1016/j.trip.2020.100095
13. "Adolescents' attitudes and intentions to use a smartphone app to promote safe driving" [Transportation Research Interdisciplinary Perspectives, 2020; 4: 100090] https://doi.org/10.1016/j.trip.2020.100090
14. "Perceived safety and experienced incidents between pedestrians and cyclists in a high-volume non-motorized shared space" [Transportation Research Interdisciplinary Perspectives, 2020; 4: 100094] https://doi.org/10.1016/j.trip.2020.100094
15. "Pathways to sustainable urban mobility planning: A case study applied in São Luís, Brazil" [Transportation Research Interdisciplinary Perspectives, 2020; 4: 100102] https://doi.org/10.1016/j.trip.2020.100102

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