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The price elasticity of parking: A meta-analysis

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ABSTRACT

The effect of parking fees on parking demand has been investigated in many different contexts, applying a wide variety of study designs. Research that brings together the knowledge derived in these studies systematically, however, is scarce. We conduct a meta-analysis of parking price elasticities based on 50 studies. Using seemingly unrelated regression models we account for the interdependence between the price elasticity of occupancy (EPO), dwell time (EPD), and volume (EPV). We show that estimates of parking elasticities based on stated preference (SP) data lead to different managerial and policy insights than estimates based on revealed preference (RP) data. Given a large amount of reported and unreported variation between the existing studies on parking price elasticities, we provide concrete recommendations for future studies that should warrant a higher degree of comparability and coherence in research design, conduction, and reporting.

1. Introduction

Whether the objective is profit maximization or traffic management, knowing the price elasticity of parking demand is of vital importance to various groups of stakeholders, including policymakers, urban planners, transport authorities, garage operators, and facility managers (Inci, 2015). Underpriced parking stimulates individual car usage as it reduces the generalized cost of traveling by car. The most prominent side effect is congestion added by cruising cars, which can make up a significant share of total traffic within a city (see Shoup, 2006); the additional traffic, in turn, adds greenhouse gas emissions and air pollution. Parking pricing policies thus have substantial power in decreasing these negative externalities (a.o., Arnott et al., 1991; Verhoef et al., 1995; Anderson and De Palma, 2004; Shoup, 2005).

In this paper, we state expected ranges for the price elasticity of parking occupancy (EPO), the price elasticity of parking dwell time (EPV), and the price elasticity of parking volume (EPV), based on a meta-analysis of existing studies. Past literature reviews have mainly focused on the estimation of the EPV (Feeney, 1989; Concas and Nayak, 2012). Even though empirical knowledge on the EPO is of high importance for policymakers in order to reduce cruising traffic (Shoup, 2005),[1] this paper is the first to generalize its effect size, and to state an expected range.[2] Also the EPD, which moderates the effect of an increase in (hourly) parking prices on parking demand (Nourinejad and Roorda, 2017), has so far received little attention.

Feeney (1989) was probably the first to conduct a comprehensive review of the impact of parking fees on parking demand. His

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[1] There are different possibilities to manage parking occupancy, such as optimizing parking supply, changing pricing or implementing parking restrictions (e.g., maximum parking times). The increase of parking supply in cities is often not possible due to spatial constraints.

[2] Recently, scholars have put more emphasis on studying the EPO (Kelly and Clinch, 2009; Farber and Weld, 2013; Madsen et al., 2013; Hoss, 2014; Milosavljević and Simićević, 2014; Zhang, 2014; Cats et al., 2016; Gragera and Albalate, 2016).

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work includes simple but very crucial considerations of what should be considered when comparing parking price elasticities. He points out that motorists can respond in multiple ways to parking policies (by changing parking location, mode, trip timing, trip destination or by abandoning the trip). Based on his considerations it can be concluded that when comparing price elasticities of parking it is important to control for the number and types of travel responses that are under analysis. Due to the limited number of studies on price elasticities of parking at the time the study was conducted (1989), a conclusion on the expected range of the EPV could not be drawn.

Concas and Nayak (2012) conduct a meta-analysis of the EPV based on 169 parking demand elasticity estimates from 25 studies. They are the first to estimate an expected range of the EPV based on a meta-analysis. They find that the average price elasticity for the US is −0.39 (−0.86 for non-US countries). Their work, however, ignores the thoughts of Feeney (1989) concerning the importance of substitutes. While Feeney (1989) distinguishes between mode choice models and parking location choice models, Concas and Nayak (2012) combine them in their statistical analysis without controlling for possible differences. We will discuss differences between our findings and those derived by Concas and Nayak (2012) in Section 6 of this paper.

This study contributes to the academic debate by summarizing the knowledge derived by other surveys on the EPO, the EPD, and the EPV in a systematic way. To determine expected ranges and to investigate and explain the variation found in the literature, a meta-analysis is conducted. The results described in this paper should also help policymakers in designing more efficient parking policies geared towards optimizing parking occupancy.

We estimate a seemingly unrelated regression model with cross-equation restrictions (SUR-CER) to account for correlations between the three elasticity types and to impose the restriction that the EPO equals the sum of the EPD and the EPV, which should hold under controlled conditions. Not much research has been conducted on the interplay between the EPO, the EPD, and the EPV, neither from a theoretical nor an empirical perspective. However, recent work by Nourinejad and Roorda (2017) hints at the relevance of this interplay for correctly predicting the reactions of travelers to changes in parking prices.

The paper is organized as follows. In Section 2, we review potential determinants of the price elasticity of parking based on the existing literature. Section 3 provides an overview of the data; i.e., the papers entering our meta-analysis. Section 4 introduces the modeling framework, including the regression setup and variable definitions. We present the estimation results in Section 5. Section 6 discusses and summarizes the results of the meta-analysis. Section 7 provides recommendations for conducting future studies on price elasticities of parking and corresponding meta-analyses.

2. Determinants of parking price elasticities

Every single price point on a consumers' aggregate demand curve is associated with a price elasticity. Given a downward sloping demand curve, price elasticities increase (in absolute terms) if parking prices increase. As mentioned in the introduction, in the context of parking, we distinguish between the price elasticity of parking occupancy (EPO), the price elasticity of parking dwell time (EPD), and the price elasticity of parking volume (EPV). The EPO states the impact of a change in price on parking occupancy, the EPD on dwell time, and the EPV on parking volume. Parking price elasticities are usually studied for a specific setting, which may be defined by a shared location, price and/or parking regulations for all parking lots or drivers under investigation. Examples are garages or metered on-street parking within a specific district. Parking price elasticities are likely to differ substantially across these settings.

2.1. Relation between the EPO, the EPD and the EPV

Under controlled conditions, the price elasticity of parking occupancy (EPO) equals the price elasticity of parking dwell time (EPD) plus the price elasticity of parking volume (EPV), as parking occupancy is the ratio between consumed parking hours (spaces per period) and supplied parking hours. However, the data may not always reflect this relation due to measurement and calculation issues. For instance, measuring parking occupancy using (ticket) vending machine data vs. floating car data may lead to different results if some drivers (legally or illegally) do not pay for parking (Cats et al., 2016). Furthermore, reported parking occupancy can be computed as the ratio of the averages or the average of the ratios. Only for the former case, it holds true that the EPO equals the EPD plus the EPV. In the context of RP data, it is furthermore important to realize that measured parking occupancy is not a linear function of parking demand, but rather of consumed parking. The latter is parking demand truncated by supply restrictions. Besides physical limits (parking occupancy cannot be higher than 100%), parking regulations may impose supply restrictions.

The interplay between the three elasticity types has only been investigated more thoroughly in recent years. To our best knowledge, so far only four empirical studies have investigated changes in parking utilization, volume, and occupancy following a parking price change. In Kelly and Clinch (2009) and Hoss (2014), where all three elasticities have been computed using the same measurement method, the EPO is indeed the sum of EPD and EPV. In Milosavljević and Simićević (2014) and Cats et al. (2016) this relationship does not hold true. Milosavljević and Simićević (2014) states a lower (in absolute terms) EPO than EPV for the first price change (despite a positive EPD). The EPO reported by Cats et al. (2016) is lower (in absolute terms) than the EPD (despite a negative EPV). The latter study measures parking occupancy with calibrated vending machine data, while the calibration is based on comparisons with floating car data.

Two recent studies indicate that a high EPD may lower the EPV. In a theoretical model, Nourinejad and Roorda (2017) show that an increase in (hourly) parking prices may lead to an increase in demand if the EPD is high: as a result of shorter parking durations the availability of parking lots improves attracting additional users. Simićević et al. (2012a) points out that drivers who are able and willing to shorten their parking dwell time are more likely to continue parking after an increase in the hourly parking fee.

In the next section, we discuss supply- and demand-related determinants of parking price elasticities in more detail in the following two subsections.

2.2. Supply-related determinants of parking price elasticities

When parking demand in a specific area exceeds parking supply (resulting in a parking occupancy of close to 100%), parking occupancy will react less to price changes than if parking occupancy is low. In the case of decreasing prices, parking occupancy is likely to remain close to 100%. The implied EPO is zero. In the case of increasing prices, the EPO will be less elastic than in contexts with occupancy rates of less than 100%, as freed up parking space will be consumed by latent demand, and may even attract new groups (e.g. due to a reduction of search time) (Milosavljević and Simićević, 2014). If dwell times remain constant, also the observed EPV will be less elastic in contexts with high occupancy.

Parking elasticities based on stated preference (SP) data may be more elastic than parking elasticities based on revealed preference (RP) data. Parking elasticities can be measured based on hypothetical data (SP) or real-life data (RP). While RP studies typically examine consumed parking, SP studies gauge parking demand. As occupancy close to 100% is a common motivation for parking price increases (and hence RP studies), parking demand is likely to be close to or even exceed parking supply in many RP-based studies. We thus expect that EPOs and EPVs derived from SP data might be higher (in absolute terms) than those derived from RP data. For the EPD this issue is less relevant as latent demand probably has little effect on dwell times. Moreover, parking dwell time limits can be made explicit in SP experiments.[3]

2.3. Demand-related determinants of parking price elasticities

The demand for parking within an area equals the sum of requested parking hours (spaces per period) of all consumers who wish to park at a specific price level. The consumers' available substitutes, budget constraints, and individual preferences influence parking demand. The activity associated with the parking event might affect individual preferences for parking. As the price of parking increases, the demand for parking will generally decrease, all other factors being equal.

The price elasticity of any good or service is affected by the extent to which substitutes are available and the characteristics of those substitutes. The availability of close alternatives will ceteris paribus imply a higher price elasticity. We can group the available behavioral alternatives into (1) substitutes with no (or minor) effects on the underlying activity associated with the parking event, and (2) substitutes that do affect the underlying activity associated with the parking event. Group (1) includes changes in the parking location and the mode of transport. Group (2) contains changes in the parking dwell time (and hence the duration of the activity), changes in the timing of the activity, changes in the location of the activity, or abandonment of the activity.

2.3.1. Substitutes

The available parking alternatives may have the most substantial effect on the price elasticity of parking compared to other behavioral options. An alternative nearby parking space with similar characteristics is the closest substitute. In a thought experiment, Shoup (2006) showed that the curb parking price elasticity of on-street cruising time (as well as the off-street parking price elasticity of on-street cruising time) is only affected by the curb parking price and the off-street parking price. Indeed, the EPV can be extremely elastic if plenty of curb-parking and off-street parking is available and the price gap between both parking types is small (Charles River Associates Inc., 1984; Kobus et al., 2013).

In the case where alternative transport modes have similar qualities as cars, drivers may consider switching to other modes when parking prices increase, and no close parking substitutes are available. Ceteris paribus, car usage increases when parking prices decrease. Indications that the level of transit service affects the price elasticity of parking are given by Dueker et al. (1998). Specifically, they show that the number of commuters who would hypothetically give up commuting to work by car due to an increase in parking fees depends on the quality of the available transit service quality. The higher the transit service quality, the higher the share of people willing to give up commuting by car. Finally, drivers will reduce their parking dwell time if the marginal parking fee exceeds the marginal utility associated with the corresponding activity.

2.3.2. Budget constraints

The costs of parking are generally only a small fraction of the overall income. In those studies that enter our meta-analysis, the average parking costs per hour as a fraction of daily GDP per capita are 3.1% (our analysis only includes paid parking). Hence, we expect the income effect of parking to be only marginal. An exception may be recurring trips with long parking dwell times, such as commuting trips. For a ten-hour workday, the parking costs as a fraction of daily GDP per capita based on our data are 13.0%. The price elasticity of parking for commuting trips may, therefore, be more elastic than for non-commuting trips. It is, however, true that the time of work, work location and work itself cannot be substituted easily, as switching costs are high.

The parking fee structure, i.e., the time interval in which charges are paid, may substantially affect the EPD. Parking providers often offer long-term contracts with unlimited parking for a monthly, seasonal or yearly charge. This is especially common for parking at work or residential parking. In contrast, on-street parking or parking at shopping malls is mostly paid in short-term (ten to sixty minute) intervals. If the charging interval is greater than the driver's maximum dwell time at the lower price, a change of

[3] We found no study measuring the price elasticity of parking dwell time using SP data.

parking fees will not affect the dwell time (e.g. often true for parking at work). In this case, the EPV equals the EPO.

3. Data collection and characteristics

3.1. Search

We collected price elasticities of parking[4] from published and non-published papers written in English as input for this meta-analysis. A threefold search strategy has been applied in order to gather empirical papers on the price elasticity of parking. First, papers cited in previous literature reviews (Feeney, 1989; Vaca and Kuzmyak, 2005; Concas and Nayak, 2012; Madsen et al., 2013) were used as a starting point. We found more studies using forward- and backward-citation search. Second, we conducted a keyword search.[5] We searched papers on the Science Direct database (Elsevier) and Google Scholar. Third, 52 experts were asked (via E-mail) to send or refer us to articles on the price elasticity of parking. They were also asked to indicate other experts, to whom we then sent the same request. The initial experts were selected based on the studies mentioned in the above-cited literature reviews. 27 of those experts responded. In total, seven additional papers cited by those experts were included into the analysis.

3.2. Selection

In total, 181 observations from 50 papers (which are all listed in Table 1) have been identified as adequate for being included in the meta-analysis. A complete observation reports an EPO, an EPD, and an EPV. It states the effect of a parking price change on parking occupancy, dwell time and volume. However, only 6 observations are complete, as shown in Table 1. All observations together report 21 EPOs, 6 EPDs and 166 EPVs, which are in sum 193 elasticities. We take into account multiple observations per paper if the paper investigates and reports the elasticities for price changes in different geographical or temporal settings, or if it states multiple elasticities associated with different price points.

In papers that make use of multiple estimation methodologies, we only use elasticities that are based on the primary model. The primary model is defined as the one with the highest adjusted log-likelihood, adjusted fit or – if the former two are not reported – best fit. To minimize uncontrolled variance in the meta-analysis, we only select elasticities based on the whole sample if the information provided in the paper allows for it.[6] Table 1 shows how each article is categorized and which elasticity values are used. The table also includes information on the explanatory variables used in the meta-regression, which we introduce in more detail in Section 4.2.

We have excluded elasticities and papers with the following characteristics from our analysis:

- Price elasticities at a price of zero (Espino et al., 2007; Farrell et al., 2005; Hess, 2001; Miller and Everett, 1982; Newmark and Shiftan, 2007; Shoup and Willson, 1992; Washbrook et al., 2006; Willson and Shoup, 1990; Willson, 1992): they cannot be converted to point or log-arc elasticities.
- Papers based on secondary data with the primary data being used in other studies that enter our meta-analysis (Abboud, 2006; Axhausen and Polak, 1991; Bu and Pershouse, 2015; de Jong et al., 1999).
- Papers with strong endogeneity in prices (Kimley-Horn and Associates, 2011; Ottosson et al., 2013; Pierce and Shoup, 2013; Shriver, 2016; Pu et al., 2017).[7]
- Elasticities in the presence of very close substitutes (Charles River Associates Inc., 1984; Kobus et al., 2013).[8]
- We exclude a very large EPV of -6.22 reported in Clark and Allsop (1993), which is based on a sample of 29 self-selected employees of the University College London.
- We exclude an observation with a reported positive EPV of 1.04 from Cats et al. (2016). This positive EPV may be partially due to a simultaneous parking fee change in the city center.
- Lee (2000) is excluded as it is the only paper that uses a "backward" arc price elasticity.[9]
- Papers reporting elasticities for locations with special demand structures (Kanafani and Lan, 1988).[10]
- Papers for which individual elasticities (see Section 3.3) could not be calculated, as the authors do not report the sample means

[4] Residential parking is not part of this analysis, as parking at home does not share the same substitutes as parking events associated with specific activities (work, leisure/social activities, shopping, etc.).

[5] The following keywords were used: parking fee elasticity, parking fee sensitivity, parking price elasticity, parking price sensitivity, parking toll elasticity, parking toll sensitivity, parking tariff elasticity, parking tariff sensitivity, parking tax elasticity, parking tax sensitivity, parking space utilization, parking space occupancy, parking demand sensitivity, parking price sensitivity, parking dwell time elasticity, parking duration elasticity, parking volume elasticity.

[6] For instance, Simićević et al. (2012b) states EPVs for different trip purposes.

[7] Data of those studies where obtained from zones with performance-based parking policies, where prices are adjusted according to the previously measured level of parking occupancy.

[8] In Charles River Associates Inc. (1984), drivers switched to close substitutes (in terms of location, mode and timing) after a parking price increase in a garage during the morning peak. Kobus et al. (2013) report very high EPVs (in absolute terms) of -5.5 for on-street and -2.2 for off-street parking for a one-hour parking activity. In their study, on-street and off-street parking were very close substitutes with nearly equal prices.

[9] Backward elasticities (elasticities based on generalized travel costs and not just parking fees) are lower than point or arc elasticities for downward-sloping demand curves.

[10] Kanafani and Lan (1988), for instance, investigate parking elasticities at an airport.

Table 1
List of primary studies used (the variables are defined in Section 4.2).

Paper	Observations	Range of price elasticities			Number of observations								
		EPO	EPD	EPV	EPO	EPD	EPV	No mode choice	No parking choice	Commuting trip	Price relative to GDP	Stated preferences	Aggregate elasticity
Albert and Mahalel (2006)	1			−1.20	0	0	1	0	0	1	0.22%	1	0
Anderson et al. (2006)	1			−0.80	0	0	1	1	0	0	0.84%	1	0
Azari et al. (2013)	2			−0.22/−0.20	0	0	2	0	0	0	0.97%	2	0
Barla et al. (2012)	1			−0.15	0	0	1	0	1	0	0.12%	1	1
Cats et al. (2016)	1	−0.86	−2.38	−0.25	1	1	1	0	0	0	2.68%	0	0
Chaniotakis (2014)	2			−1.37/−1.22	0	0	2	2	0	0	2.50%	2	0
Clark and Allsop (1993)	9			−2.40/−0.13	0	0	9	0	9	9	0.17/1.55%	9	0
Danwen et al. (2010)	6			−0.29/−0.05	0	0	6	0	6	0	7.64/15.27%	0	0
Dueker et al. (1998)	22			−0.31/−0.03	0	0	22	0	22	22	0.25/0.95%	0	0
Espino et al. (2007)	1			−0.02	0	0	1	0	1	0		1	1
Farber and Weld (2013)	1	−0.33			1	0	0	0	0	0	1.28%	0	0
Ferguson (1999)	3			−0.70/−0.10	0	0	3	2	1	3	4.28%	0	0
Fullerton et al. (2015)	1			−0.41	0	0	1	0	0	0	0.20%	0	0
Gillen (1977)	2			−0.38/−0.31	0	0	2	0	2	2	2.10%	0	1
Gillen (1978)	6			−0.53/−0.24	0	0	6	6	0	0	NA%	0	0
Gragera and Albalate (2016)	3	−1.19/−0.77		−1.11	2	0	1	1	0	0	0.78/3.92%	0	0
Hensher and King (2001)	6			−1.78/−0.48	0	0	6	0	0	0	4.87/8.94%	6	3
Hess and Polak (2004)	9			−1.20/−0.42	0	0	9	9	0	0	2.01/7.62%	9	0
Hess (2001)	2			−0.12/−0.07	0	0	2	0	2	2	0.12/0.21%	0	0
Hilvert et al. (2012)	2			−0.65/−0.33	0	0	2	2	0	0	1.59/3.82%	2	0
Hoss (2014)	2	−0.33/−0.19	−0.17/−0.07	−0.17/−0.12	2	2	2	0	0	0	2.12%	0	0
Hulme-Moir (2010)	1			−0.57	0	0	1	0	0	1	0.33%	1	1
Jeihani et al. (2015)	4			−2.73/−1.07	0	0	4	0	0	0	0.98/2.94%	4	0
Kelly and Clinch (2009)	1	−0.52	−0.42	−0.11	1	1	1	0	0	0	1.84%	0	0
Khodaii et al. (2010)	1			−0.02	0	0	1	0	1	0	1.69%	1	0
Kulash (1974)	6			−0.91/−0.08	0	0	6	0	0	3		0	0
Kunze et al. (1980)	1	−1.20			1	0	0	0	0	0	1.07%	0	0
Kuppam et al. (1998)	4			−0.17/−0.12	0	0	4	0	4	4	0.15/0.54%	4	0
Madsen et al. (2013)	2	−0.69/−0.41			2	0	0	0	0	0	0.72/1.61%	0	0
Miller and Everett (1982)	3			−0.23/−0.12	0	0	3	0	0	3	0.18/0.33%	0	0
Milosavljević and Simićević (2014)	2	−1.26/−0.60	−0.34/−0.14	−1.09/−0.89	2	2	2	0	0	0	3.90/6.23%	0	0
Newmark and Shiftan (2007)	6			−2.06/−0.50	0	0	6	0	6	0	2.16/9.35%	6	0
Ng (2014)	2			−0.70/−0.45	0	0	2	0	0	2	0.47/0.62%	0	2
van Ommeren and Russo (2014)	1			−0.02	0	0	1	0	0	1	0.20%	0	0
van Ommeren and Wentink (2012)	2			−0.97/−0.44	0	0	2	0	0	2	0.37%	0	0
Qi (2014)	1			−1.37	0	0	1	0	0	0	2.27%	1	0
Shiftan and Golani (2005)	8			−0.16/−0.02	0	0	8	0	8	0	0.30/0.89%	8	0
Shiftan (1999)	3			−1.14/−0.49	0	0	3	0	3	0	2.01/3.92%	3	0
Shoup (1992)	5			−0.61/−0.08	0	0	5	0	0	5	0.21/0.79%	0	0
Shoup and Willson (1992)	1			−0.53	0	0	1	0	1	1	0.59%	0	0

(continued on next page)

Table 1 (*continued*)

Paper	Observations	Range of price elasticities			Number of observations								
		EPO	EPD	EPV	EPO	EPD	EPV	No mode choice	No parking choice	Commuting trip	Price relative to GDP	Stated preferences	Aggregate elasticity
Simićević et al. (2012a)	1			−0.12	0	0	1	0	0	0	5.26%	1	0
Simićević et al. (2012b)	8			−0.49/−0.30	0	0	8	0	8	4	3.24/6.18%	8	0
Simićević et al. (2013)	4			−1.10/−0.03	0	0	4	0	4	0	3.98/13.52%	4	0
Teknomo and Hokao (1997)	3			−0.86/−0.44	0	0	3	3	0	0	2.22/3.51%	3	0
Van der Waerden et al. (2016)	1			−0.34	0	0	1	1	0	0	2.36%	1	0
Washbrook et al. (2006)	1			−0.30	0	0	1	0	1	1	0.35%	1	0
Weis et al. (2011)	2			−1.34/−0.64	0	0	2	0	2	0	1.17%	2	0
Widmer et al. (2015)	14			−0.69/−0.09	0	0	14	8	12	2	0.24/0.35%	14	0
Willson (1992)	1			−0.50	0	0	1	0	1	1	0.74%	0	0
Zhang (2014)	9	−0.29/−0.17			9	0	0	0	0	0	1.36/2.35%	0	0

(Tsamboulas, 2001; Golias et al., 2002).

3.3. Data conversion

Price elasticities can be derived from observing price and the corresponding demand at multiple price points, or from an econometric model capturing the effects of a price change on demand. In the first case, the point elasticity (at the new or the old price), the arc elasticity (also referred to as mid-point elasticity), or the log-arc elasticity formula can be used. In the second case, for linear econometric models (e.g. OLS) the elasticity equals the price coefficient. For econometric models with discrete dependent variables (e.g., binomial regression, multinomial regression), the price coefficient has to be converted into an elasticity using the individual or the aggregate formula: the individual elasticity computes the elasticity at the mean of the explanatory variables. The aggregate elasticity (or weighted elasticity) is calculated for the specific distribution of each independent variable and then aggregated (Westin, 1974). Elasticities computed using the individual formula tend to be higher (in absolute terms) than elasticities calculated using the aggregate method.[11]

For the analysis conducted in this paper, all elasticities based on observed price changes are converted to log-arc elasticities (with the exception of 4 observations, for which this is not possible. We therefore included them without conversion) in order to enhance comparability. The log-arc elasticity is defined as the elasticity of one variable with respect to another between two given points, where ϵ is the calculated elasticity, $Q0$ the old demand, $Q1$ the new demand, $P0$ the old price, and $P1$ the new price. The log accounts for the non-linearity of the demand curve:

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$$\epsilon = \frac{\log(\frac{Q1}{Q0})}{\log(\frac{P1}{P0})}, \tag{1}$$

The log-arc formula is also used in the case that papers report only elasticities based on predictions derived from underlying econometric models. This applies to 12 observations in our sample.

For papers based on econometric models with discrete dependent variables that do not state the aggregate nor the individual elasticity, we derive the individual elasticity based on the following formula:

$$\epsilon = \beta \times (1 - q) \times p, \tag{2}$$

where β is the estimated regression coefficient for the parking price, q is the share of the demand (regression estimate) at sample means and p is the sample mean of the parking price.

Overall, 29.0% of elasticities (56 out of 193 observations) were not provided in the papers, but had to be calculated by the authors of this paper, using the information provided in the underlying paper.

4. Models

A meta-analysis is a systematic approach to investigate existing parking price studies (Glass, 1976). It is used to synthesize and compare results from various studies. Numerous meta-analyses have been conducted in transportation economics, among others with the aim to investigate the price elasticity of gasoline demand (Espey, 1996, 1998; Graham and Glaister, 2002; Goodwin et al., 2004; Brons et al., 2008), demand for air-travel (Brons et al., 2002), public transportation demand (Nijkamp and Pepping, 1998; Kremers et al., 2002; Litman, 2004; Holmgren, 2007) and parking demand (Concas and Nayak, 2012). For a meta-analysis that – similar to this paper – controls for substitutes see Brons et al. (2002).

The primary objective of this study is to estimate general and robust range for all three parking elasticity types (EPO, EPD, and EPV) as a function of variables related to the context and design of the underlying study:

$$\begin{aligned} EPO &= \alpha_{EPO} + \beta_{EPO} X_{EPO} + e_{EPO} \\ EPD &= \alpha_{EPD} + \beta_{EPD} X_{EPD} + e_{EPD} \\ EPV &= \alpha_{EPV} + \beta_{EPV} X_{EPV} + e_{EPV}, \end{aligned} \tag{3}$$

where α is the constant, β indicates the coefficient vector, X the corresponding explanatory variable matrix, and e the error term vector for the EPO, the EPD, and the EPV, respectively.

The error terms of the three equations may be correlated. A change in the parking price might lead to a change in occupancy, dwell time and volume, as argued in Section 2.1. This correlation can be captured using a seemingly unrelated regression model. In

[11] Under the assumption that the majority of the drivers' decisions lie on the concave part of the logit function in choice models (which is usually the case), the individual price elasticities tend to be higher (in absolute terms) than the aggregate (or weighted) price elasticities (McFadden, 1974; Westin, 1974).

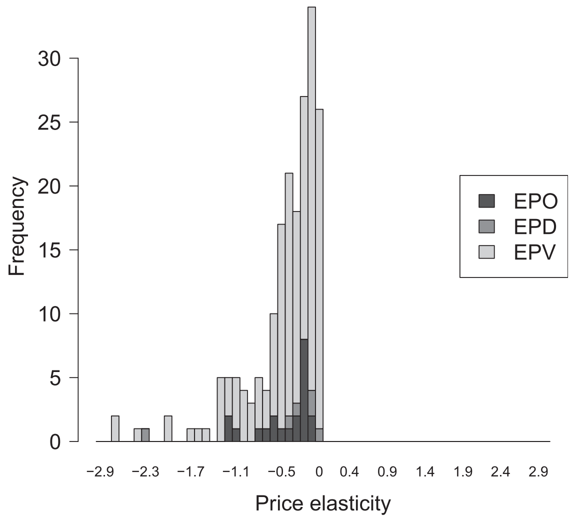

Fig. 1. Stacked histogram of the price elasticity of parking occupancy, dwell time and volume.

Section 2.1, we also state that under controlled conditions the EPO is the sum of the EPD and the EPV. This linear dependency can be accounted for by cross-equation restrictions. We describe the specification of our three main models in Section 4.4.

4.1. Dependent variables

The means of EPO, EPD and EPV in our sample are −0.5 (sd: 0.36), −0.59 (sd: 0.89) and −0.50 (sd: 0.51), respectively. The distribution of all dependent variables is shown in Fig. 1, showing that most EPO, EPD, and EPV values are inelastic; i.e., they are smaller than 1 (in absolute terms). There are no positive elasticities in our data.[12]

4.2. Independent variables

- **No mode choice** is a dummy variable measuring the availability of mode alternatives. If this variable equals 1, the corresponding price elasticity of parking has been reported without including mode alternatives. This is for instance the case for SP experiments that were designed in such a way that participants were not asked to decide between mode alternatives, or for RP studies that analyze the effect of a price change at a specific location.
- **No parking location choice** [npc] is a dummy variable measuring the availability of parking alternatives. This variable equals 1 if the corresponding parking elasticity has been reported without including parking location alternatives. This is for instance the case for SP surveys that were designed without parking alternatives, or for RP studies that do no differentiate between parking locations, or in which no parking alternative was available.[13]
- **Commuting trip** is a dummy variable and indicates parking events at the end of a trip between one's residential and work location.
- **Price relative to GDP** measures the parking price per hour relative to the country's average daily GDP per capita.[14] The daily GDP per capita is used as a proxy for available income. All parking fees were converted to an hourly rate[15]: we divide the parking fees by 10 for fees reported per day, 200 for fees reported per month and 2,000 for fees reported per year.[16,17] For 7.2% of the elasticities, prices are missing. We set them to the sample mean in order to be able to take into account the corresponding

[12] In some settings positive price elasticities can be expected. First, the EPV may be positive if a price increase leads to shorter dwell times, but - due to latent demand - an increase in parking volume (see for instance Nourinejad and Roorda, 2017). Second, reported elasticities can also be positive due to omitted variables, such as a simultaneous parking fee decrease (increase) in a neighboring region, which may pull (push) demand into (from) the neighbor region from (into) the observed region. Third, reported elasticities can be positive due to measurement errors.

[13] 3.6% of all elasticities are measured in situations without mode and parking location choice (all from SP studies), while 36.3% are measured in situations with both mode and parking location choice.

[14] We were not able to use the drivers' actual income nor the sample's mean income, as both numbers were not available for the majority of studies.

[15] 40.3% of all observations are reported per hour.

[16] Converting parking fees to hourly prices may be fraught with some problems. We conducted robustness checks by testing different sets of assumptions concerning the "conversion rate" between hourly, daily, monthly and yearly rates. Furthermore, we tested if including the price unit as a dummy variable affects the results. The dummy variables were not significant. With the exception of one EPO, all fees associated with the EPO and the EPD are charged per hour. Based on these checks, we can conclude that the proposed conversion is acceptable for our purpose.

[17] 60.2% of all observations with prices not reported per hour are commuting trips.

Table 2
Overview of explanatory variables used in the model estimations.

Variable	Total	EPO	EPD	EPV
No mode choice	35(10)	1(1)	0(0)	34(9)
No parking location choice	95(20)	0(0)	0(0)	95(20)
Commuting trip	69(19)	0(0)	0(0)	69(19)
Price relative to GDP	3.1%	2.2%	3.1%	3.2%
Stated preference	96(26)	0(0)	0(0)	96(26)
Aggregate elasticity	9(6)	0(0)	0(0)	9(6)
Observations (Papers)	193(50)	21(9)	6(4)	166(46)

observations in the regression analyses. The variable was normalized to its mean value (3.1%).

- **Stated preference** is a dummy variable equal to 1 if the elasticity observation is based on SP (rather than RP) data.
- **Aggregate elasticity** is a dummy variable being equal to 1 if the elasticity observation obtained from a regression model is calculated using the aggregate formula (see Section 3.3).

Table 1 provides information on the explanatory variables for each paper separately, whereas Table 2 gives a more condensed overview of all explanatory variables. The latter states how often each explanatory variable is provided in the data, and in how many different papers a specific elasticity is stated.

4.3. Publication bias

We use a funnel plot as a visual aid for detecting precision and publication bias (Duval and Tweedie, 2000). Fig. 2 plots the price elasticities against the corresponding sample size. We only include SP observations, as RP and SP studies generally use different sample size definitions. RP studies usually define the sample size as the number of observed parking events, while SP studies typically refer to the number of respondents in the SP survey as sample size. Furthermore, many RP studies did not state the sample size.[18] The focus on SP also implies that only the EPV observations are included, since there are no SP-based observations for the EPD and the EPO in our dataset (see Table 2). From Fig. 2, we can observe no publication bias for the SP-based EPVs. When SP- and RP-based elasticities are pooled, the mean of all EPVs stated in published papers (SP and RP) is −0.38 (sd: 0.40), and the mean of all EPVs stated in unpublished papers (SP and RP) is −0.68 (sd: 0.59), again implying no significant difference. The results are similar for the EPO: the mean for published papers is −0.91 (sd: 0.29) and that of unpublished papers is −0.38 (sd: 0.28); all EPD observations are published. We than expect that also for RP-based EPOs and EPDs no publication bias is evident.

4.4. Model estimation

As introduced in Eq. (3), we have a set of three linear equations. The independent variables (as described in Section 4.2) are: commuting trips, substitutes (no mode choice, no parking choice), price (relative to GDP) and data source (stated preference). Finally, we also control for the aggregate computation method (see Table 2). However, note that most of these variables can only be included in the EPV model, but not in the EPO and the EPD models as there are insufficient observations of these variables for EPO and EPD.

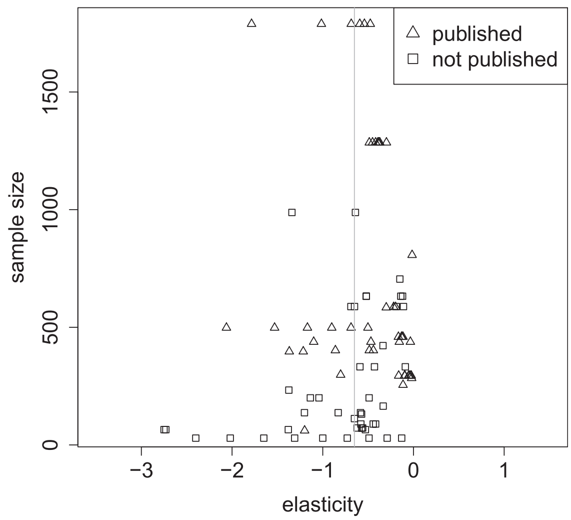

Fig. 2. Funnel plot for the price elasticity of parking volume (EPV) against sample size (for SP studies). The vertical line indicates the average.

Only the independent variable “price relative to GDP” has sufficient observations for all three equations.

In the *first* model, we estimate the three equations stated in Eq. (3) independently in a standard ordinary least squares (**OLS**) setup.

In the *second* model, we estimate all three equations simultaneously, using a seemingly unrelated regression (**SUR**) model. For a given observation, a change in occupancy, dwell time and volume is associated with a specific price change. The SUR model accounts for potential correlations between EPO, EPD and EPV by correlating the errors across the three equations for a given observation (Zellner, 1962; Henningsen and Hamann, 2007).

In the *third* model, we do not only account for the interdependence between the EPO, the EPD, and the EPV by imposing an unstructured correlation but restrict the model more strongly. As argued in Section 2.1, under controlled conditions the EPO equals the sum of EPD and EPV. The **SUR-CER** model[19]) imposes this restriction on the constant and on all coefficients, as shown in Eq. (4):[20]

$$\alpha_{EPO} = \alpha_{EPD} + \alpha_{EPV} \tag{4}$$

$$\beta_{EPO} = \beta_{EPD} + \beta_{EPV}$$

Note that since the independent variable “no mode choice” is observed for the EPOs and the EPVs, but not for the EPDs, the SUR-CER restricts the corresponding coefficient to be equal for the EPO and the EPV.

5. Findings

For better comparability between the three models for a given elasticity type, we present them separately for the EPO (Table 3), the EPD (Table 4) and the EPV (Table 5). We find that most of the results are in line with the hypotheses outlined in Section 2. The constants in the EPO and the EPV models are significantly negative in all model specifications. In the SUR specification, the constant in the EPO model is considerably higher than the constant in the EPV model, which is consistent with the EPO being the sum of the EPV and the EPD under controlled conditions (in the OLS model, the two constants do not significantly differ from each other). The central finding of the SUR-CER model is that the constant in the EPD model is significantly negative (unlike in the other two models). Generally, the standard errors of all coefficients decrease in the SUR models compared to the OLS models.[21] Note that by definition, the mean squared error (MSE) in the SUR models is higher than in the OLS model, as the SUR models are more restricted.

The EPV for commuting trips is significantly higher (in absolute terms) than for non-commuting trips. This result may indicate that for commuting trips there is a stronger income effect than for non-commuting trips. As outlined in Section 2.3.2, the income effect is expected to be higher for commuting trips than for non-commuting trips: potential savings from commuting trips are higher since parking at work is a regularly recurring event with long parking dwell times (based on this study’s data we estimate that the average costs of parking at work are 13.0% of daily GDP per capita and business day, assuming a ten-hour workday). Our finding also implies that the income effect outweighs a potential substitution effect, which would render commuting elasticities lower (in absolute terms) due to a lack of substitutes regarding trip destination and dwell time.

We estimate a significantly negative coefficient for the “price relative to GPD” variable for all EPO and EPV models, reflecting the negative gradient of the parking demand curve (i.e. parking price elasticities increase (in absolute terms) with rising prices). For the EPD, this holds true only in the SUR-CER specification, whereas the coefficient corresponding to the “price relative to GPD” variable is insignificant in the OLS and SUR model (at the 5% level). However, the better fit of the SUR-CER model compared to the SUR (the MSE amounts to 1.18 and 1.50, respectively) provides an indication that also for the EPD the gradient of the parking demand curve may be negative.

We find that, on average, the EPV obtained from SP experiments is more elastic than the EPV obtained from RP experiments. Besides the potential prevalence of hypothetical bias (Fifer et al., 2014), supply restrictions may cause differences between SP- and RP-based elasticities. In real life, not all drivers may be able to satisfy their parking requirements due to supply restrictions (i.e., occupancy cannot be higher than 100%). SP studies typically do not account for supply restrictions and latent demand, but assume that all parking demand can be satisfied. Although SP studies tend to investigate short-run elasticities,[22] and RP studies tend to focus on situations that describe long-run equilibria, this temporal distinction does not seem to be the main explanation between the divergence of SP- and RP-based elasticities, as in that case we would expect lower SP (i.e., short-run) than RP (i.e., long-run) elasticities.

The use of the aggregated calculation method exhibits no significant effect on the EPV in any of the models (at the 5% level); but only nine observations are computed based on the aggregated calculation method.

Table 6 shows the 95% confidence interval of the EPO, the EPD, and the EPV for non-commuting and commuting trips based on

[18] The different sample size definitions as well the fact that many studies do not state sample sizes are also the main reasons for not controlling for sample size in our regression models.

[19] A similar approach has been used by Brons et al. (2008).

[20] A two-sided paired t-test does not reject this relation. However, the test is only based on 6 observations.

[21] In an alternative specification, we cluster the standard errors per paper for the OLS model, which however, leads only to slight changes in the standard errors.

[22] SP studies usually refer to a specific choice situation (often with attribute levels pivoted around a situation that is familiar to the respondent) and do not frame the choice situation as one that occurs repeatedly.

Table 3
Regression models on EPO (standard errors in brackets).

	OLS	SUR	SUR-CER
Constant (EPO)	−0.64***	−0.58***	−0.63***
	(0.09)	(0.05)	(0.05)
No mode choice	0.00	−0.10	0.17*
	(0.34)	(0.13)	(0.07)
Price relative to GDP	−0.15*	−0.10**	−0.14***
	(0.06)	(0.03)	(0.03)
MSE	0.10	0.11	0.10
Observations	21	21	21

Note: $^{\cdot}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 4
Regression models on EPD (standard errors in brackets).

	OLS	SUR	SUR-CER
Constant (EPD)	−0.59	−0.47	−0.30***
	(0.40)	(0.25)	(0.08)
Price relative to GDP	0.05	0.43.	−0.12***
	(0.26)	(0.16)	(0.03)
MSE	0.97	1.50	1.18
Observations	6	6	6

Note: $^{\cdot}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 5
Regression models on EPV (standard errors in brackets).

	OLS	SUR	SUR-CER
Constant (EPV)	−0.35***	−0.34***	−0.33***
	(0.09)	(0.07)	(0.07)
No mode choice	0.22*	0.22**	0.17*
	(0.10)	(0.07)	(0.07)
No parking location choice	0.35***	0.35***	0.34***
	(0.08)	(0.06)	(0.06)
Commuting trip	−0.20*	−0.20**	−0.20**
	(0.09)	(0.07)	(0.07)
Price relative to GDP	−0.03**	−0.03***	−0.03***
	(0.01)	(0.01)	(0.01)
Stated preference	−0.55***	−0.55***	−0.55***
	(0.08)	(0.06)	(0.07)
Aggregate elasticity	0.21	0.21.	0.20.
	(0.15)	(0.11)	(0.12)
MSE	0.18	0.18	0.18
Observations	166	166	166

Note: $^{\cdot}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

the results of the SUR-CER model.[23] We use the SUR-CER model as baseline model due to the underlying modeling assumptions being most consistent with theory as well as the plausibility of the estimated coefficients. Note that our sample does neither include SP observations of the EPO and the EPD nor RP observations for the EPO and the EPD for commuting trips. For commuting trips we

[23] Confidence intervals are calculated at the sample mean, except for the variables "no mode choice" and "no location choice", which are set to 1.

Table 6
Theoretical (in italics) prediction and confidence interval of the EPO, the EPD and the EPV for commuting and non-commuting trips based on the results of the SUR-CER model.

	RP		SP	
95% confidence intervals	Lower	Upper	Lower	Upper
Commuting trips				
EPO *(theoretical prediction)*	*−0.63*	*−0.41*	*−1.23*	*−0.90*
EPD *(theoretical prediction)*	*0*	*0*	*0*	*0*
EPV	−0.63	−0.41	−1.23	−0.90
Non-commuting trips				
EPO	−0.72	−0.54		
EPD	−0.46	−0.15		
EPV	−0.45	−0.18	−0.98	−0.75

assume that the EPO equals the EPV, as the EPD for commuting trips is probably close to zero. This assumption allows us to make the theoretical prediction that the EPO equals the EPV for commuting trips (see Table 6). Commuters will probably not or only marginally change their time spent at work in the case of parking price changes, due to work time restrictions.

We see in Fig. 3 how elasticities depend on the availability of mode and parking choice alternatives. The elasticities are highest (in absolute terms) when drivers can switch to mode and parking alternatives, and lowest when neither of these alternatives exists. This pattern holds for both, commuters as well as non commuters.

6. Discussion & summary

This meta-analysis summarizes the results of 50 papers on parking price elasticities. We use a seemingly unrelated regression models to account for dependencies between the price elasticity of occupancy (EPO), dwell time (EPD) and volume (EPV). Our main model includes cross-equation restrictions, assuming that the EPO equals the sum of the EPD and the EPV, a relation that should hold under controlled conditions. For non-commuting trips we obtain a baseline EPO of −0.63 (c.i.: −0.72/−0.54) based on RP data, which consists of an EPD of −0.30 (c.i.: −0.46/−0.15) and an EPV of −0.32 (c.i.: −0.45/−0.18). For commuting trips the baseline EPO is −0.52 (c.i.: −0.63/−0.41) based on RP and −1.07 (c.i.: −1.23/−0.90) based on SP data. It equals the baseline EPV for commuting trips, as we assume that the EPD for commuting trips is negligible.

The estimates for the EPO based on RP data indicate that generally there is a high potential to raise revenues of on-street parking and garages by increasing parking fees. The potential to raise revenues is also high for commuter parking. Predictions based on SP data yield a less optimistic picture for commuter parking, with the EPO not being significantly lower than 1 (in absolute terms).

As mentioned in Section 2.2 of this paper, RP estimates may be smaller (in absolute terms) than SP estimates due to latent demand being present in RP settings. As a result of this potential downward bias in RP-based elasticities, it is thus generally preferable to use SP-based coefficients in situations with (peak) occupancy rates significantly lower than 100% (provided that the SP experiments are well designed and realistic, in turn reducing the prevalence of hypothetical biases). Parking at work is usually reserved parking and thus not subject to latent demand. As a consequence, RP estimates collected in the context of commuting will not be biased by latent demand.

We show that it is important to control for drivers' substitutes and the price associated with a specific elasticity when comparing the price elasticity of parking between studies. Our findings further indicate that stated preference (SP) estimates of the EPV are

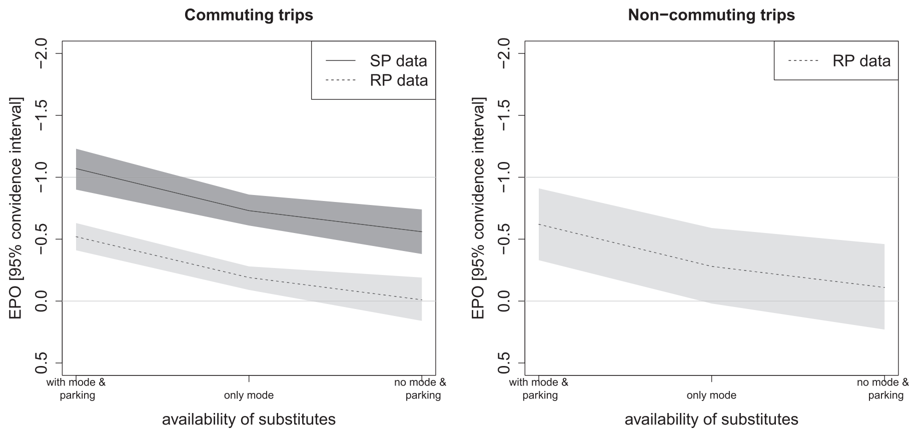

Fig. 3. EPO predictions by the availability of substitution.

significantly higher (in absolute terms) than revealed preference (RP) estimates. RP estimates may be downward biased due to latent demand.

Even though the higher number of elasticities considered in our paper compared to earlier meta-analyses of parking elasticities allows us to state an expected range for the elasticities, we must still conclude that parking price elasticities are widely context-dependent and that the number of observations included in our meta-analysis seems insufficient to capture the full heterogeneity present across study contexts. In turn, this also renders the result of meta-analyses somewhat susceptible to the characteristics of the underlying studies. The high heterogeneity across studies might partially explain why our results diverge from those of Concas and Nayak (2012), which is based on 25 studies, along some dimensions. Most strikingly, we report (based on 50 underlying papers) that EPVs from SP studies are higher (in absolute terms) than EPVs from RP studies, while Concas and Nayak (2012) find the opposite pattern.

7. Recommendations for future research on parking price elasticities

Conducting this meta-analysis has been challenged by widely different ways of computing and reporting (or in many cases, not reporting) parking price elasticities in the underlying studies. For instance, many elasticities had to be (re-)computed by the authors of this paper, based on the (sometimes sparse) information provided in the underlying papers, which unavoidably introduces additional variance to the data (as described in Section 3.3).

In order to render future studies concerning parking price elasticities more comparable, we advise scholars to adhere to common research and reporting standards:

1. In order to better understand the behavioral reactions to parking price changes, the available choice alternatives and their characteristics should be analyzed and reported. Preferably, also the model itself should control for these alternatives, as they are likely to affect the estimated elasticities.
2. The way how elasticities are computed should be stated explicitly. For elasticities based on observed price (and demand) changes, the arc-log elasticity is advisable. Elasticities based on econometric models should be calculated employing the individual and aggregate formula (see Section 3.3).
3. The papers should contain the sample means, or preferably distributions of the variables used in the underlying econometric models. This allows readers to (re-)calculate the corresponding elasticities.
4. It is generally preferable to investigate the willingness to pay for parking rather than the elasticity associated with a single price change, as the former carries more generic information.
5. Finally, it is advisable for researchers to put empirical findings in relation to recent theory-based insights.

Apart from a higher number of underlying papers with a high quality of research design, conduction and reporting (as described in the above paragraph), the following factors may render the results of future meta-analyses of parking price elasticities more accurate:

1. Including quality features of parking and mode substitutes may lead to valuable insights on how substitutes and price policies should be coordinated to manage traffic effectively. Detailed data on characteristics of substitutes were not available for most existing studies.
2. The price elasticity of parking is highly specific to individual circumstances and land use. We approximate income by including the parking price per hour relative to the country's average daily GDP per capita. We did not control for other socioeconomic or demographic factors that might affect the elasticities.
3. Parking occupancy has a strong effect on the EPO and the EPV (a likely reason for the difference between SP and RP elasticities). We do not directly control for parking occupancy due to a lack of observations.
4. Due to a lack of data, elasticities were calculated independently from the generalized costs of travel, which would take into account also other travel-related cost components. The ratio of parking costs and generalized costs might affect the parking price elasticity.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2019.01.014.

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