



# Nobody can pay the right price for parking: It's time to change the system

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## ABSTRACT

The existing parking system assumes that drivers can pay the right price for parking, but we find the opposite in a field study (N = 567) and a survey study (N = 474). Drivers either overpaid or underpaid for parking at on-street parking meters 94 % or 98 % of the time, in the survey study and field study respectively, for 20–30 min on average in the field study. Such misalignment between parking payments and presumed price can mask the price signal and reduce its ability to influence drivers' behavior and downstream environmental consequences. We also find that the public prefers an alternative, intelligent payment system that automatically collects on-street parking fees based on actual parking durations. These findings provide evidence for widespread parking payment inaccuracy and suggest an opportunity for public policy and technology to address the problem. This research offers important insights for transportation and planning professionals on the future of parking.

## 1. Introduction

In most cities, parking meters require drivers to pay ahead of time based on an estimate of how long they will park. If they return later than expected, they can receive a ticket; if they return earlier than expected, they do not receive a refund for the extra time for which they paid. Unless one pays exactly the right amount for parking every time, one will always lose money in the parking system. It is doubtful, however, that drivers *can* pay the right price for parking. Each year, an average parking consumer in the U.S. leaves behind \$100 of unused parking fees, and one in five drivers receives a parking ticket, totaling \$20.4 billion in extra parking fees and \$2.6 billion in parking tickets (Cookson and Pishue, 2017). We do not know how frequently drivers make a wrong parking payment.

Why does inaccurate parking payment matter? We argue that aside from the unfair financial burdens placed on drivers, parking payment inaccuracy matters because aligning drivers' payments with parking prices sharpens the effect of price on drivers, which means the parking system can effectively use pricing to influence drivers' behavior and downstream transportation and environmental outcomes.

How do we combat the problem of payment inaccuracy? We argue that it's time to abandon the requirement for drivers to estimate parking duration. This study supports joining policy and technology to create an alternative parking payment system, one that automatically collects

payment based on actual parking duration through geo-location and mobile technologies. If policy and technology can eliminate payment inaccuracy, then the parking system would require fewer citations to manage parking. The system could be designed to increase the power of pricing to motivate optimal parking behavior, mitigate downstream transportation consequences, and ultimately, benefit the public.

This article presents two case studies of on-street metered parking payment behavior based on field data collected in Denver, Colorado and a national survey study conducted in the U.S. The cases present evidence that challenges the assumption that drivers can pay the right price for parking most of the time. The two studies examine the frequency, magnitude, and intentionality of parking payment inaccuracies, as well as public support for an automatic duration-based payment system.

The next section describes the current state of research and policy for parking payment decisions. We also present a theoretical framework, based in psychology and behavioral economics, that explains why predictable biases in drivers' parking payment decisions would be problematic for parking policy and management. Section three outlines the data collection and analytical strategies we used to develop two case studies of parking payment behaviors and decisions. Section four presents the results of both studies. The final section interprets the results with an emphasis on how the design of future parking systems could be improved by attending to the observed patterns in parking payment behavior.

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## 2. Literature and background

Parking payment decision making is complex, poorly understood, and understudied. The peer-reviewed transportation, economics, and engineering literatures present analyses of the driver's parking search decisions empirically and analytically, but the driver's parking payment decisions have rarely been addressed (Inci, 2015; Arnott, 2014). Most existing research on parking payment decisions assumes that the driver is rational in their decision to pay and by extension that any lack of compliance with parking payment rules is intentional (Cullinane, 1993). Or the research treats the driver as a black box, examining the fact of a payment with little exploration of the underlying decision making (Yang and Qian, 2017). Our goal for this study was to open the so-called black box to observe and analyze behavioral patterns of parking payment decisions, including payment non-compliance.

### 2.1. Parking pricing as a tool to influence behavior

Overall, parking prices in the U.S. have been too low, which encourages driving and traffic in congested downtown areas, leading to an overreliance on cars, excessive emissions, and urban sprawl (Shoup, 2011). Extensive research shows that setting higher parking prices in congested areas, combined with better public transportation options, can optimize parking distribution, parking availability, reduce cruising for open parking spaces, reduce traffic in congested areas, and encourage environmentally-friendly modes of travel (Shoup, 2011; Shoup, 2018). To accomplish these goals, cities have increasingly used parking pricing to influence travel decisions, setting higher prices in places and at times where parking demand is high to discourage drivers from driving and parking their vehicles, and lower prices where demand is low to redirect vehicles to these areas (San Francisco Municipal Transportation Agency SFMTA, 2016; San Francisco Municipal Transportation Agency SFMTA, 2014). A critical assumption of this approach, however, is that the price set by the system is the price being paid, so that drivers will be incentivized by the variation of prices across different areas.

The problem with this assumption is that the metered parking system requires drivers to pay for parking based on their *estimated* parking duration instead of their *actual* parking duration. There is no mechanism to guarantee that drivers do not overpay, and no real system to guarantee that they do not underpay either. The system's only tool is the threat of post hoc punishment for underpayment, in the form of a citation. Citations could deter underpayment, but they also create an incentive for overpayment. If drivers' parking payment frequently deviates from the set price, either overpaying or underpaying, then parking price incentives will be masked and not felt as directly and sharply by drivers. And if actual parking payments deviate randomly and frequently from set parking prices, the price signal loses its effect on drivers' behavior and other downstream consequences.

So, do drivers mostly pay the right price for parking, or do they frequently fail to do so? This question is the focus of the current research, which we answer through a field study and a national survey study.

### 2.2. The existing parking payment system and alternatives

First, let's examine the existing parking payment system. The existing approach to metered parking payment—charging drivers based on their *estimated* parking duration—provides ample opportunity for inaccurate payment because drivers can overestimate or underestimate how long they will need to park their vehicle. Historically, a deterrence approach based on citations for underpayment or lack of payment was necessary, as there were no alternative technologies to ensure parking payment (Adams and Webley, 1997). Drivers could simply walk off without paying for parking if they were not required to pay ahead of time. Transportation research has studied other types of deviant

behaviors, such as parking in loading zones, sidewalks, or handicapped spaces, as well as speeding (Oliveira and Lúcia, 2016; Morillo and Campos, 2014; Cope et al., 1991; Suarez de Balcazar et al., 1988; Rothengatter, 1982). In these examples, the deviant transportation behavior is subject to deterrence through surveillance and enforcement, which involve tradeoffs between the cost of administration and benefits in terms of desired behavioral outcomes (Lei et al., 2017; Shoup, 2011; Black et al., 1993a; Gibbs, 1986).

Next, imagine an alternative approach: Charging drivers based on actual parking duration through automatic detection of parking time and location, as well as automatic transactions. This would preemptively ensure that all payments are accurate by default. Today, this alternative approach is feasible. Precise geolocation makes it possible to detect actual parking duration for a specific vehicle at a precise parking location; widespread use of mobile banking means that fee collection can occur automatically. These technologies are already used in the parking system for other purposes such as monitoring parking occupancy. The newer smart parking systems rely on sensors to detect and monitor the status of parking spaces in real time. Additionally, the system would, in theory, be able to detect payment non-compliance in real time and allow citations to be issued remotely (Sadhu Khan, 2017). The future scenarios may be further complicated by changes in vehicle technologies that could lead to vehicles simply cruising in a semi-parked status as they wait to pick up passengers (Millard-Ball, 2019).

So, why haven't cities adopted these technologies to make parking payment accurate and automatic? A major problem, we argue, is the assumption that people *can* make the perfect parking payment if they try hard enough. Even the most modern and "smart" parking systems still operate under this assumption (Black et al., 1993a,b; San Francisco Municipal Transportation Agency SFMTA, 2014). However, decades of research in psychology and behavioral economics demonstrates that human decisions are often imperfect and irrational despite best intentions, making certain expectations of behaviors unrealistic (Tversky and Kahneman, 1974; Tversky and Kahneman, 1981; Gigerenzer and Goldstein, 1996; Kahneman, 2011). For example, it is likely that drivers *overpay* the meter to avoid the small chance of receiving a parking ticket due to distorted risk perception (Tversky and Kahneman, 1981). Drivers may also *underpay* the meter due to planning fallacy—the universal tendency to underestimate how long it takes to complete a task, in this case, the business drivers need to take care of before returning to the meter (Buehler et al., 1994). These tendencies are part of how humans behave, yet the current parking system does not account for these systematic imperfections in human behavior.

## 3. Methods

We conducted two studies. Study 1 was a field observational study with 567 parking events in Denver, CO, and Study 2 was a survey study on self-reported parking behavior among 474 U.S. drivers. Both studies obtained approval from the Colorado Multiple Institutional Review Board. Informed consent was exempt in Study 1 and was obtained for Study 2. All data and materials are posted on Open Science Framework at <https://osf.io/pbdq8/>.

### 3.1. Study 1

In study 1, we observed payment behavior at parking meters on a sample of 42 block faces in the Denver Lower Downtown (LODO) area for two or three hours each time during weekdays (when parking meters require payments) over three weeks in spring 2018. The study area is located within Denver's central business district where there is demand for parking throughout the day. The total study area is bounded by 14th Street, Wynkoop Street, 20th Street, and Arapahoe Street. It comprised a total of 41 blocks and 74 block faces (a block face is one side of a street, and each street has up to two block faces for metered parking).

### 3.1.1. Sampling strategy

To select a sample of block faces and time periods for the field study, we calculated the annual average occupancy rate from municipal meter transaction data (2015–2016), which represented a census of transactions at parking meters in our study area between 8:00 a.m. – 9:00 p.m. We used the parking occupancy rate to achieve two goals: 1) select a sample of block faces that represented variation in parking occupancy across the study area; and 2) select periods during the day that represented differences during peak versus off-peak hours. We note that the municipal meter transaction data have a major limitation: parking occupancy rates are based on the purchased parking time and the data do not represent the time a vehicle actually occupied a parking space. We used it for the purpose of deriving a sampling strategy for Study 1 as this was the best available data on parking occupancy in the study area.

The sampling strategy included four steps: selecting block faces, selecting hours, assigning block faces to different observation hours, assigning block faces to different days during the week. We first randomly selected 10 block faces from each quartile of block faces in the occupancy rate distribution (from among the 74 block faces), totaling 40 block faces as our target for data collection in Study 1. Note that some block faces were omitted before random selection process because our initial inspection of the study area showed that the meters had been covered and were unavailable for parking.

Next, we graphed the hourly occupancy rate of meters for each of the 40 block faces in the sample (based on the secondary meter transaction data) to observe the fluctuation in occupancy rate with time during the day. Visually, all four graphs indicated two peak time periods: 11:00 a.m. – 2:00 p.m. and 5:00 p.m.–8:00 p.m. In addition, they indicated an off-peak time period 8:00 a.m. – 11:00 a.m., when the occupancy is comparatively low. Therefore, we included three time periods of three hours each: two peak periods (11:00 a.m. – 2:00 p.m. and 5:00 p.m.–8:00 p.m.) and one off-peak period (8:00 a.m. –11:00 a.m.) in the field study. The two peak time periods allowed us to include parking events with potentially different purposes, with the 11:00 a.m. – 2:00 p.m. period possibly representing more business-related travel, and the 5:00 p.m.–8:00 p.m. period possibly representing more leisure-related travel (entertainment and dining).

Subsequently, within each quartile (10 out of the 40 block faces in the sample), we assigned four block faces for observation during 8:00 a.m. – 11:00 a.m., three block faces for observation during 11:00 a.m. – 2:00 p.m., and three block faces for observation during 5:00 p.m.–8:00 p.m.

Finally, each block face was randomly assigned to one the five weekdays for observation to remove any variation of parking behavior based on the day of the week. Three block faces were not observed due to logistical issues, or the parking meters being covered after the sampling strategy was determined. Thus, only 37 block faces that we initially included in the sampling strategy were observed in Study 1.

Note that we also conducted a pilot test from Feb 28 – March 13, 2018, on five block faces in the study area for two-hour periods each, which occurred before finalizing the sampling strategy. The goal of the pilot study was to confirm that the data collection instrument and data collection protocol worked under various parking conditions. Two out of the five block faces we observed in the pilot study were sampled again for our field study. Although the pilot study led us to shift from two hours to three hours for each observation period, to maximize sample size we included these pilot data in the final data set.

### 3.1.2. Field data collection

The data collection occurred during a three-week period from April 2 – April 20, 2018. Each block face was observed on the day of the week as assigned but could be observed on any week of the three-week period.

The field data collection focused on the entire timeline of each parking event. Upon arriving to the site, research assistants confirmed that each of the parking meters was functioning and recorded baseline data for each meter (paid parking time left on meter, vehicle description

of any parked vehicles, any citations). After completing the census of the existing parking events, research assistants observed arrivals and departures of all vehicles on the block face during their assigned three-hour field study session. Each data collection instrument was turned in after the field session, scanned, and then the data were entered into a spreadsheet. Table 1 lists the variables recorded in the field data.

Field data collection yielded N = 957 total observed parking events, but 43 had recording errors (neither arrival nor departure were recorded) and were removed from the analysis, leaving a total of 914 correctly recorded parking events.

### 3.1.3. Imputation

Because the field study captured only a three-hour period (two hours in the pilot), and vehicles could arrive before or leave after the study period, some arrival and departure time information was missing. Of the 914 correctly recorded parking events, only 375 had both arrival time and departure time recorded. If we used only the 375 complete parking events in our analysis, however, we would introduce bias by focusing on relatively shorter parking events, because longer parking events may have been removed due to arrivals before the observation period started or departures after the observation period ended.

To overcome this bias, we implemented hot deck imputation to estimate missing arrival time. We did not impute missing vehicle departure time. This is because the secondary meter transaction dataset does not record the actual vehicle arrival and departure time, but instead, records when the driver made the meter payment, and when the meter expired. Drivers usually pay for the meter within a few minutes after arrival, so meter payment time from the secondary dataset is a good proxy for true vehicle arrival time. However, because drivers could return to their vehicle long before or much after the meter expired, meter expiration time from the secondary data is an inferior representation of the vehicle’s true departure time. Thus, the secondary meter-transaction dataset allows us to impute vehicle arrival time relatively accurately but does not provide an accurate method to impute vehicle departure time.

Because of our decision to impute missing arrival time only, of the 914 correctly recorded parking events from Study 1, our main analysis used a subset of 567 parking events where the departure time was

**Table 1**  
Variables recorded for parking events data in Study 1.

Variable	Description
Study date	Date of field observation
Study start time	Start time of field observation period
Study end time	End time of field observation period
Name of recorder	Name of individual collecting the data
Street name and block face	Location and block face being observed
Pole number	Individual meter where the parking event occurred
Vehicle description	Key feature of vehicle observed, e.g., color, type
Arrival time	Vehicle arrival time
Time of payment	Time of meter payment
Time on meter post payment	Time on meter after the payment
Time of second payment additional payments)	Time of second payment, if applicable
Time on meter post second payment (repeated for 3rd, 4th or any additional payments)	Time on meter after second payment, if applicable
Departure time	Vehicle departure time
Time on meter post departure	Time remaining on meter after departure
Time inherited	Amount of time inherited by a driver parking in a space with time left on a meter from a previous parking event
Time of surveillance	Time when parking enforcement passed by
Citation issued during observation	Indicate whether any parking citations were issued during the parking event
Notes	Notes
Reason for “did not record” if applicable	Notes regarding any information not observed and/or recorded

observed. Of the 567 parking events in our final analysis, 192 parking events had missing vehicle arrival time information, which we imputed. To impute for missing arrival times for these 192 parking events, we used the secondary meter payment transaction data set and assumed a correspondence between the time of meter payment and the true arrival time. From the secondary meter payment dataset, we first identified the population of vehicles which, at exactly 8:00 a.m., 11:00 a.m., or 5:00 p.m. (the beginning of the three time periods of data collection in Study 1) on any day of between Oct 2015–Sep 2016 (period of meter transaction data in the secondary dataset), were parked on the same block face as the vehicles we observed in Study 1 that had missing arrival times.

Within this population of parking records in the secondary dataset, we then focused on the time of the meter transaction and expiration time (ignoring the day and date), and identified all the records that satisfied two conditions: 1) the parking record in the secondary dataset had a meter expiration time that occurred within +/- 15 min of the departure time of the parking event we observed in Study 1 we wanted to impute, 2) the parking record in the secondary dataset had a meter payment time that was earlier than the beginning of the Study 1 field observation session for the parking event we wanted to impute (and therefore would represent an arrival time that wouldn't have been observed during the study session).

Based on the records that satisfied these criteria, we constructed a cumulative distribution function of the meter payment time (as a proxy for arrival time). We drew five random data points from this distribution function and took the mean as our imputed arrival time.

Note that the imputed arrival time helps correct the bias introduced by the limited three-hour observation periods, i.e., having complete data for shorter parking events. However, for reasons discussed above, our analysis did not impute missing vehicle departure time. This means our imputation method does not fully correct the bias of including shorter parking events than real-world parking events. That is, our data will show a conservative estimate of vehicle parking durations.

To summarize, from the original N = 914 usable observations we created a working data set of N = 567 with observed departure time. This final dataset includes 375 parking events with observed arrival times and 192 parking events with imputed arrival times.

### 3.2. Study 2

Study 2 recruited 514 adult U.S. drivers who had parked at a meter in the past 24 h from Amazon Mechanical Turk, an online survey recruiting site, to participate in an online survey. The study was conducted during five consecutive weekdays from April 26 – May 2, 2019, recruiting about 100 participants each day. The online survey asked participants about their most recent parking experience within the past 24 h. We focused on parking experience from the past 24 h to maximize accuracy in participants' recall of their parking events. We collected data during the weekdays because many parking meters often only charge fees during weekdays.

#### 3.2.1. Participants

A total of 514 participants were screened into the survey based on the two screening questions on whether they had parked in an enforced meter in the past 24 h. Of these participants, 474 passed an attention-check question at the end of the survey and were included in the analysis. These 474 participants came from 169 metropolitan areas and 47 states. The sample had a mean age of 33.84 (SD = 9.23), was 62 % male, 37 % female, and 1 % gender queer or nonconforming; median education was the bachelor's degree, median household income was between \$50,000–\$74,999, and 78 % were white (Table 2).

#### 3.2.2. Questionnaire

Online survey participants first answered two screening questions: 1) SQ1: During the past 24 h, did you park a car at a meter during its enforcement hours? (Yes; No; I don't remember); 2) SQ2: Did you also

**Table 2**  
Summary of demographic information of participants in Study 2.

	Response (N = 474)
Age (Mean)	33.84 (SD = 9.23)
Min-Max	18–74
Gender	
Male	62.2 %
Female	36.5 %
Trans female/Trans woman	0.2 %
Trans male/Trans man	0 %
Gender queer/Gender nonconforming	0.8 %
I prefer not to answer	0.2 %
Highest degree obtained (Median)	“Bachelor's degree”
Less than a high school graduate	0.4 %
High school graduate or GED	10.3 %
Some college or education beyond high school	21.7 %
Associates or technical degree	11.0 %
Bachelor's degree	45.1 %
Graduate degree or professional degree	11.2 %
I prefer not to answer	0.2 %
Hispanic or Latino/a	
Yes	14.6 %
No	84.0 %
I prefer not to answer	1.5 %
Race (can choose multiple)	
White	77.6 %
Black/African American	14.6 %
American Indian or Alaska Native	2.5 %
Asian	7.2 %
Other	1.3 %
I prefer not to answer	0.8 %
Household Income (Median)	“\$50,000 – \$74,999”
Less than \$10,000	4.2 %
\$10,000 – \$24,999	12.2 %
\$25,000 – \$49,999	33.3 %
\$50,000 – \$74,999	26.8 %
\$75,000 – \$99,999	14.6 %
\$100,000 – \$149,999	6.1 %
\$150,000+	2.7 %

end that parking session during the meter's enforcement hours? (Yes; No; N/A). Participants who indicated “yes” to both questions were directed to the questionnaire. The rest of the participants were told they did not qualify for the study. Note that before data analysis, participants who didn't pass a basic attention check question at the end of the survey (Q23) were also excluded from analysis.

The questionnaire included 25 questions. Questions 1–10 asked about participants' most recent parking experience at a meter in the past 24 h. Questions 11–15 asked for their preferences about different parking policies. Questions 16–22 asked for their demographic characteristics. Question 23 was an attention-check question, and questions 24–25 asked whether participants were able to remember enough information from their parking experience to answer the questions.

For the parking experience questions, we first asked participants to think about “the most recent time that you parked at a meter in the past 24 h during its enforcement hours.” Participants then indicated whether there was time left on the meter when they arrived (Q1), and if yes, whether they added money to the meter (Q2a), or if no, whether they paid the meter (Q2b). Participants also indicated their method of payment if they either added money or paid the meter. All participants then indicated the total time for which they paid the meter, including time already on the meter (Q4), and whether they knew the maximum time limit for the meter (Q5). All participants (except those who left the meter completely unpaid) also indicated how they decided how much to pay

(Q6). All participants then indicated whether they refilled the meter (Q7), whether the meter was expired when they returned (Q8, Yes/No/Just expiring at that minute), and whether they received a parking ticket (Q9). Those who received tickets indicated the reason for their ticket (Q10a, Expired meter/Exceeding the maximum time limit allowed for the meter/Other), and those who did not receive tickets indicated whether they were able to get their money back for the extra time left on the meter (Q10b).

For the parking policy preference questions, we first described a hypothetical new parking system that automatically charges people for exactly how long they park at a meter, with no possibility for overpayment or underpayment, and no parking tickets. Participants indicated whether they preferred this new system, the existing system, or had no preference either way (Q11) and were asked to explain their preference (Q12). In the next three questions, participants made a forced choice between pairs of parking policies, with brief descriptions under each policy: Autopay vs Manual pay (Q13), Tired pricing vs Fixed pricing (Q14), and No time limit vs With time limit (Q15).

The demographic questions asked about the participants' ZIP Code, age, gender, education level, ethnicity, race, and income (Q16–22). Finally, participants answered an attention-check question consisting of a short paragraph unrelated to parking (Q23) and indicated whether they were able to remember enough details from their parking experience to complete the survey (Q24), and if not, on what questions they had to guess (Q25).

#### 4. Results

Study 1 showed that of the 567 parking events we observed in Downtown Denver, only 2 % (n = 13) were paid exactly right (and two of these did not stay for more than one minute and paid nothing), 51 % (291) were overpaid, and 34 % (191) were underpaid (Fig. 1). The remaining 13 % (n = 72) did not have enough information for us to determine payment accuracy. When drivers underpaid, they underpaid for 19.38 min (\$0.32) on average, and when drivers overpaid, they overpaid for 30.68 min (\$0.51) on average (Table 1). Note that even when we relaxed the definition of payment accuracy to include events underpaid or overpaid by five minutes or less, only 19 % (108) of drivers crossed this threshold and made “approximately accurate” payments.

In addition, drivers frequently inherited leftover parking payment from a previous driver. Out of the 352 parking events for which we could measure time inheritance status, 32.4 % (n = 114) inherited time from previous drivers, each inheriting an average of 26.22 min (\$0.44) (Table 3).

Field observers noted that shorter parking events can include drivers dropping off passengers, picking up passengers, parking but not exiting

the vehicle, and drivers staying in the vehicle as they waited for passengers to go out and return, etc. Drivers who did not pay for parking out of pocket had shorter parking durations than drivers who paid, both when they inherited time (M = 18.41 vs 52.14 min, t (110) = 6.14, p <.001) and when they didn't inherit time (M = 27.59 vs 73.85 min, t (231) = 7.17, p <.001).

The ratio of total payment to total occupied time was 1.55, and the ratio of total out-of-pocket payment to total occupied time was 1.16, indicating a net effect of overpayment to the parking system.

Paradoxically the “payment compliance rate,” defined as the proportion of occupied time that was paid, was only 0.82, suggesting a seeming lack of payment compliance. This contradiction arises because the payment compliance rate focuses on the period when the vehicle occupied the parking space, and examines what proportion of this time is paid, while ignoring the time when the space is still paid for but unoccupied (overpayment). The metered parking system's emphasis on payment compliance, instead of payment accuracy, is a potential reason that the system spends substantial amount of time and money to enforce payment, whereas drivers are forced to hedge their bet by overpaying.

In Study 2 (Table 4), when survey respondents described how they decided how much to pay for parking, 64.5 % reported that they paid for more time than they expected to park, 29.8 % reported paying for exactly as long they expected to park, 2.6 % reported paying for less time than they expected to park, and another 3.2 % of participants reported paying for the maximum parking duration the meter allowed. Despite the high level of diligence, 18.4 % of drivers ended up with an expired meter upon return (underpayment), 75.3 % had extra time left on the meter (overpayment), and only 6.4 % self-reported perfect payment. In addition, 12.2 % of drivers reported receiving a parking ticket. Similar to Study 1, 42.6 % of survey respondents reported inheriting time from a previous driver.

When asked about a potential new parking payment system (Table 4), which would automatically charge for the actual parking duration, with no possibility to overpay or underpay nor any possibility for tickets, 85.4 % of drivers said they liked the new system better than the existing system. In questions comparing different features of the new vs existing parking payment systems, 85.7 % of participants preferred automatic payment to manual payment, 74.3 % preferred not having time limits to having time limits, although only 39.5 % of participants preferred tiered pricing (lower per-hour price at first, higher per-hour price later) over uniform pricing.

Our analysis also showed that acceptance of automatic, duration-based parking payment system is unlikely to be driven by participants' recent bad experience with the existing system. Whether the respondent received a parking ticket in the most recent parking experience in the past 24 h (n = 58 did vs n = 416 didn't) was not related to preference for

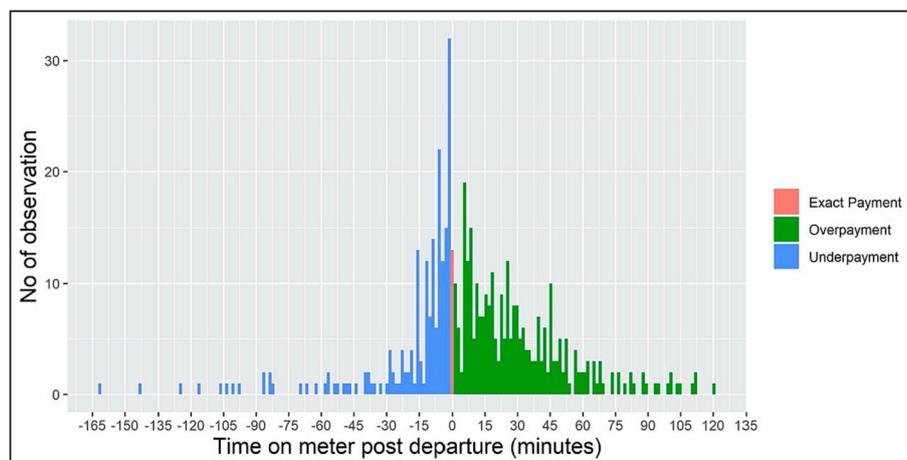


Fig. 1. Distribution of overpayment, underpayment, and exact payment in Study 1.

**Table 3**  
Summary of observed parking events in Study 1 (N = 567).

	n	Mean	Min	1st Quartile	Median	3rd Quartile	Max
Duration of stay* all users (min)	567	63.10	0.00	12.50	62.00	103.60	195.60
Inherited time all users* (min; 215 unknown)	352	8.49	0.00	0.00	0.00	10.00	96.00
Inherited time among those who inherited time* (min)	114	26.22	1.00	10.00	21.50	36.00	96.00
Underpaid time among those who underpaid* (min)	191	19.38	1.00	4.00	9.00	20.00	162.00
Overpaid time among those who overpaid* (min)	291	30.68	1.00	11.00	25.00	44.00	120.00
Out-of-pocket paid time among those who paid out of pocket (min)	277	79.92	5.00	57.00	76.00	120.00	208.00
Out-of-pocket paid time across all users* (min; 52 unknown)	515	50.10	0.00	0.00	46.00	90.00	208.00
Total out-of-pocket paid time + Inherited time* (min; 52 unknown)	515	55.91	0.00	5.00	57.00	102.00	208.00

**Table 4**  
Percentage of parking events or respondents in response category in Studies 2 (N = 474).

Behavior/Preference	N	%
<b>Meter was paid (at least partially)</b>	467	96.4 %
No time left on meter upon arrival, put money on meter	265	55.9 %
There was time left on meter upon arrival, added more money	163	34.4 %
There was time left on meter upon arrival, did not add money	39	8.2 %
Unknown whether payment was inherited or out of pocket		
<b>Meter was not paid (no time left on meter, did not pay meter)</b>	7	1.5 %
<b>Knew the meter maximum time limit at the time</b>	157	33.1 %
<b>How did you decide how much total time to pay?</b>		
I paid for exactly how long I thought I would need	139	29.3 %
I paid for more time than I thought I would need, just in case	301	63.5 %
I paid for less time than I thought I would need	12	2.5 %
I paid for the maximum amount of time I was allowed to park at the meter	15	3.2 %
<b>Fed the meter again (physically or online)</b>	78	16.5 %
<b>Meter status upon return</b>		
Meter already expired upon return	87	18.4 %
Meter was just expiring upon return	30	6.3 %
Meter was not expired upon return	357	75.3 %
(if not expired) able to get money back for extra minutes on meter	22	4.6 %
<b>Received a parking ticket upon return</b>	58	12.2 %
Ticket for expired meter	41	8.6 %
Ticket for exceeding maximum time limit	25	5.3 %
<b>Preference for a new system that automatically charges for exact parking duration, not possible to over/under pay, and no tickets</b>		
I like the new system	405	85.4 %
I do not have a preference either way	52	11.0 %
I like the existing system better	17	3.6 %
<b>Prefer auto pay over manual pay</b>	406	85.7 %
<b>Prefer tiered pricing over fixed pricing</b>	187	39.5 %
<b>Prefer no time-limit over having time-limit</b>	352	74.3 %

the new parking payment system (no parking ticket: 85.8 % vs with parking ticket: 82.8 %, Fisher’s exact test = 2.24, p = .36). If anything, those who did not receive a parking ticket showed more support for autopay than those to those who did (89.4 % vs 58.6 %),  $\chi^2$  (df = 1, N = 474) = 39.40, p < .001, and for having no time limit (78.4 % vs 44.8 %),  $\chi^2$  (df = 1, N = 474) = 29.95, p < .001. This shows that the enthusiasm participants showed for an automatic duration-based parking payment system in Study 2 is not driven by recent bad parking experiences that happened to occur prior to the study.

### 5. Discussion and conclusions

The current research found that 94 % (Study 2) and 98 % (Study 1) of consumers either underpay or overpay on-street parking meters. In addition, 32 % (Study 1) and 43 % (Study 2) of drivers inherited time from a previous driver. We do not propose a direct statistical comparison of these two studies and instead provide a critical interpretation of their results. In an overwhelming majority of parking events in each study, the actual payment deviates from the set parking price. The degree of deviation is not trivial, averaging about 20 min of unpaid parking for those in the field study who underpaid, and about 30 min of unused

parking fees for those who overpaid.

To see the financial impact of payment inaccuracy, we scaled up the proportion of underpayment and overpayment observed in the field study. Assume the average number of parking events during a one-year period in the Denver LODO area is represented by the 2015–2016 secondary parking transaction data, that is 683,013 parking events. Given that Study 1 observed 291 overpaid parking events and 191 underpaid parking events out of 495 parking events where payment accuracy could be computed (58.8 % and 38.6 %, respectively), this means that for the Denver LODO area alone, each year, we can expect 992,808 overpaid parking events totaling \$507,656 of overpayment, and 649,405 underpaid parking events that would expose drivers to the risk of a \$25–50 fine each time, while at the same time owing a total of \$209,758 to the city. Echoing the INRIX data we cited in section 1, this level of parking payment inaccuracy within just a small area of downtown Denver justifies its salience as a public problem.

Our findings have two implications. First, we argue that it is unfair for on-street metered parking systems to punish drivers for inaccurate payments. This problem arises because of the system’s deterrence framework, which posits that underpayments are rational and therefore intentional. Our results point to the opposite conclusion. Our data suggest that parking payment inaccuracy is prevalent and usually unintentional. Drivers’ stated payment strategy in Study 2 strongly indicates that they mostly intend to pay for their estimated parking duration, or even more; and when payment inaccuracies occur, they are more often in the form of overpayment than underpayment. That is, drivers are mostly diligent in paying the right price, but still make mistakes almost all the time. It is unfair to punish drivers for payment mistakes they did not intend to make and cannot possibly avoid even if they tried. The parking payment system design should be revised to recognize the unrealistic expectations of drivers.

Second, and more importantly, payment inaccuracy can mask the existing price variations on which parking systems rely to shape parking behavior. For example, San Francisco invested \$20 million in the smart SF Park program. A key action of SF Park involved adjusting the hourly parking price by \$0.25 every-three months in response to fluctuations in demand ( San Francisco Municipal Transportation Agency SFMTA, 2014). Given the \$0.33–\$0.50 of payment inaccuracy that we have observed in Study 1, the \$0.25/hour price variation could be easily drowned out by the noise of payment imprecisions and fail to incentivize drivers’ behavior. This calculation is likely an underestimate of payment inaccuracy in San Francisco. The per-hour parking price is lower in Denver than San Francisco, and assuming the same overpaid or underpaid duration in parking events in both cities, the payment inaccuracy is likely larger (in dollar amount) in San Francisco, and thus more likely to drown out the system-designed payment variations set by SF Park. If cities are serious about using dynamic pricing to regulate parking and its downstream consequences in traffic, space, and travel mode choice, payment imprecision is a problem that is too large to ignore.

Several technology options that could enable an automatic, duration-based parking payment system are not just on the horizon, but already here. With increasing vehicle automation, a duration-based automatic payment system could prepare cities for an adaptive, smart, and connected transportation system.

The problem of parking payment inaccuracy is serious, a potential solution is near, and the driving public may support it. Our recommendation to cities: pilot programs that replace traditional on-street parking meters with systems that charge based on actual parking duration.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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