MOUNTAIN-PLAINS CONSORTIUM

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IRRATIONALITY IN METERED PARKING PAYMENT COMPLIANCE

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16. Abstract

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Irrationality in Metered Parking Payment Compliance

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September 2022

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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). Drivers either overpay or underpay for parking at on-street parking meters 98% of the time, for 20–30 minutes on average. Such misalignment between parking payments and presumed price can mask the price signal and reduce its power to influence drivers' behavior and downstream environmental consequences. These findings provide evidence for widespread parking payment inaccuracy and suggest a way forward for change. This research offers important insights for transportation and planning professionals on the future of parking.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

When you park at a parking meter, do you carefully estimate how long you expect to be away from your car? Do you pay the maximum parking fee as a rule? Do you pay as little as you can get away with, or not at all, especially if you expect to return to the car momentarily? Parking payment decision making is complex, poorly understood, and understudied. Most existing research on parking payment decisions either 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 it 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.

In most cities, parking meters require drivers to pay ahead of time based on their estimate of how long they will need to park. If they return later than expected, they can receive a ticket; if they return earlier than expected, they cannot get a refund for the extra time they paid for. The only way to not lose in this parking game is to pay the exact amount for parking duration every time. However, it is doubtful that drivers can pay the right price for parking. Each year, an average driver 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, however, what proportion of parking events have payment inaccuracies, that is, how frequently drivers make a wrong parking payment.

Why does accurate parking payment matter? After all, is it not a good thing that cities can receive extra revenue from inaccurate parking payment, either from extra parking fees or from citations, to invest in other public projects? We argue that aside from the obvious unfair financial burdens placed on drivers, parking payment inaccuracy matters for a bigger reason: whether or not drivers' payments align with the parking price can greatly impact the transportation system, as well as downstream environmental outcomes.

The parking payment decision has implications beyond payment compliance and is particularly relevant for smart parking programs. For example, in 2011, San Francisco, California, launched SFPark, a smart parking pilot program that implemented demand-responsive pricing, communication technology, and street-level hardware to better manage on-street metered parking. An evaluation of the pilot program observed that drivers were only paying for parking about 50% of the time. This situation begets the question: how can price influence parking decisions if people do not always pay for parking? To effectively use pricing to influence parking behavior, we must understand what is involved in parking payment decisions.

This report presents a study of on-street metered parking behavior based on data collected in Denver, Colorado. The study involved observing real on-street parking behavior in the city's central business district, supplemented with information from the city's administrative records of on-street parking meter payment transactions.

2. LITERATURE

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). In recent examples where parking payment has been examined, it was used indirectly to improve estimates of parking space occupancy rates and traffic congestion (Yang and Qian, 2017; Petiot, 2004). Based on our review of the literature, parking payment behavior has not been examined as an important parameter in the design of parking systems.

Certain social psychology, economic, and transportation studies, however, have considered parking payment non-compliance as an example of social deviance that should be subject to deterrence (Adams and Webley, 1997). Other types of deviant behaviors observed in the transportation system included parking in loading zones, sidewalks, or handicapped spaces, as well as speeding (Barracho Oliveira, 2016; Morillo and Magín 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. Surveillance and enforcement decisions 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).

A major limitation of the existing studies on parking payment non-compliance, including within the deterrence model, is that they assume perfect rationality, arguing that people do not pay for parking if it is not in their economic interest (Shoup, 2011; Black et al., 1993a; Black et al., 1993b). This is typical of most public policy analyses, which assume that people will make rational decisions about social problems based on the cost-benefit ratio of alternatives.

Recent decades of research in psychology and behavioral economics, however, has shown that real behaviors are not perfectly rational, and sometimes they are even "irrational" (Ariely, 2008; Kahneman, 2003; Tversky and Kahneman, 1981; Tversky and Kahneman, 1974). For example, studies of child poverty prevention show that people donate more money to one identified child in need than they donate to a group of anonymous children in a similar situation (Kogut and Ritov, 2011). Similarly, we all know a story of someone buying a gym membership and never using it, even though they continue to pay for it. These behaviors are irrational; all else being equal, the needs of many children clearly exceed the needs of one child; and paying for a gym membership without using the gym is an economic loss with no benefits.

Because many other behaviors are irrational, we should not assume that parking payment decisions are necessarily rational. We should test this idea. Therefore, the objective of our research was to test the proposition that underpaying for parking, or not paying at all, makes sense under conditions of perfect rationality.

2.1 Trends in Smart Parking Technology and Payment Models

Our study of parking payment decisions focuses on on-street parking meters that accept credit cards and coins and that collect real-time data about parking transactions. The parking payment problem depends on the technological conditions at the time; parking payment mechanisms have been changing with advances in mobile technologies, so the exact nature of the problem might have different features in different regions and in future contexts.

In *The High Cost of Free Parking,* Donald Shoup describes how new technology can make managing parking substantially easier. Beyond smart meters, which can adjust prices to meet the demand, there are several other new parking solutions. Multi-space "pay-and-display" meters allow drivers to exit their vehicle and insert a pre-paid smart card into a meter, which encompasses up to 40 meters in one. Additionally, there are pay-by-space meters, with the parking space itself marked with a number, and time is purchased through a single meter holding 40 or more spaces. There are personal, in-vehicle meters, which operate with a pre-paid smart card and a small "meter" device that hangs from the rear-view mirror. More recently, city-wide smart parking systems have been proposed. If parking were part of an Internet of Things, smart parking systems would enable drivers to quickly search for and find available parking spaces near their destinations.

In terms of new technology, many drivers and municipalities are looking for ways to eliminate the need to estimate the amount of time needed. In Charleston, South Carolina, drivers use smart cards to pay for parking, and any remaining time is refunded onto the smart card for that driver to use later. Time limitations, however, were still enforced. A company in Ontario, Canada, PayBySky, uses GPS technology to charge for parking by the minute, eliminating both the need for drivers to estimate how much time they need, and eliminate the need for cities to install and maintain parking meters (Keenan, 2010). PayBySky utilizes "surge" pricing, so while a driver may overstay the time limit, instead of receiving a citation, that driver will simply pay a higher rate for the amount of time they park after the initial time limit is up. Likewise, in Sacramento, California, drivers have no time limit at meters, but "premium pricing" takes effect after the initial "base time" has been used. For example, parking for the first two hours may be $1.00/hour, but in the third hour, the rate increases to $3.00/hour.

The newer smart parking systems rely on low-cost sensors and webcams 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 (Sadhukhan, 2017). The future scenarios are further complicated by changes in vehicle technologies that could lead to autonomous vehicles simply cruising in a semi-parked status as they wait to pick up passengers (Millard-Ball, 2019).

3. RESEARCH DESIGN, DATA AND METHODS

In this study, we sought to observe and understand the decisions that people make as they pay for metered parking. Parking meter transaction data are available from local governments, but they are limited for the purpose of analyzing payment decisions because they typically provide information only about when a driver paid and how much time they paid for. What if the driver left the space early, leaving time on the meter? This type of transaction data does not reveal the duration of actual parking events or parking events that were not paid for at all. Such information is necessary for understanding the full range of parking behavior.

Because of this deficiency in secondary data, we collected primary data by observing drivers parking and paying their meters as well as their departures and the arrival of the next vehicle. The combination of field data and secondary data was useful and allowed us to achieve our analytical aims. In the following sections we describe the study area, data sources, data collection strategy and sampling procedure, and our analytical methods.

3.1 Study Area

The study area is located within Denver's central business district, in an area considered the lower downtown (LoDo) neighborhood (Figure 3.1). This neighborhood has been revitalized over the past 20 years with jobs, housing, and transportation investments, such as the Union Station transportation terminal. Therefore, there is demand for parking in this area throughout the day. The study area is bounded by 14th Street, Wynkoop Street, 20th Street, and Arapahoe Street. It comprised 41 blocks and 74 block faces. A block face is one side of a street, and each street has two block faces for metered parking, although some streets only have one block face open for parking.

3.2 Secondary Data

The city of Denver provided us with meter transaction data for October 2015–September 2016. This secondary meter transaction data show that our study area included 747 on-street parking meters. The actual number of active meters at any time varies due to construction and other events.

The municipal meter dataset included 2,097,149 payment transactions. Each coin dropped into the meter counts as one transaction, so this figure overestimates the true number of paid parking events because people may pay with several coins. To prepare the dataset, we assumed that coin transactions made within 180 seconds of each other at the same pole on the same day counted as a single event. This assumption consolidated transactions such that the total became 1,683,013.

Each payment transaction in the dataset had 13 attributes, including the time and date of payment, the meter pole and location, the amount of time purchased, and the payment type (i.e., coins, credit card; see Table 3.1).

The secondary data, however, cannot provide a complete picture of metered parking payment behavior. For example, meter payment time cannot reveal the actual arrival of vehicles because there is a delay between the time a vehicle arrives and when a person pays. Nor can the dataset reveal the actual departure times of vehicles because the next parking event usually does not occur immediately after a car leaves a space. This implies that the secondary data cannot answer questions about the duration of actual parking events and whether people overstayed their paid time. Moreover, the secondary data do not include information about people who did not pay at all. Information about the lack of payment is necessary for understanding drivers' actual payment compliance behavior. These gaps in available data motivated our field data collection.

Figure 3.1 Study area and observed parking meters, Denver, Colorado

Table 3.1 Attributes of parking payment transactions in Denver's municipal parking data

	Variable	Description
1	Time	Time of parking payment
2	Date	Date of parking payment
3	Area	The street where the parking payment was made
4	Subarea	The street block where the payment was made
5	Pole	Pole number (i.e., individual meter) where the payment was made
6	Parking end time	Time when the meter would expire
7	Time purchased	Amount of time purchased
8	Coins	Amount paid using coins
9	Bills	Amount paid using bills
10	Credit card	Amount paid using a credit card
11	Smart card	Amount paid using a smart card
12	Remote/PBP	Amount paid remotely
13	Total	Total amount paid by all payment types

3.3 Field Data

The field data collection focused on the entire timeline of parking behavior for each parking event. The field data build on the information in the secondary data and include additional variables. The variables in the field data are listed in Table 3.2 and include the actual arrival time, departure time, presence of parking enforcement (i.e., surveillance), whether a citation was issued, and time inherited from previous parking events.

We began by taking a census of the parking meters located in the study area that were operating and noted which meters had been removed or were not functioning. Next, we conducted a pilot test of the data collection instrument and data collection protocol on five block faces to confirm that it worked under various parking conditions. The data collection protocol and instrument are included in the appendices. We also used the pilot study to develop training materials for the students who would ultimately collect the field data. Based on this pilot study, we decided to extend the length of the observation period from two to three hours. In addition, we included the data collected during the pilot study in the final field dataset.

Table 3.2 Attributes of parking events in the Denver field data

	Variable	Description
1	Study date	Date of field observation
2	Study start time	Start time of field observation period
3	Study end time	End time of field observation period
4	Name of recorder	Name of individual collecting the data
5	Street name and block face	Location and block face being observed
6	Pole number	Individual meter where the parking event occurred
7	Vehicle description	Key feature of vehicle observed, e.g., color, type
8	Arrival time	Vehicle arrival time
9	Time of payment	Time of meter payment
10	Time on meter post payment	Time on meter after the payment
11	Time of second payment	Time of second payment, if applicable
12	Time on meter post second payment	Time on meter after second payment, if applicable
13	Departure time	Vehicle departure time
14	Time on meter post departure	Time remining on meter after departure
15	Time inherited	Amount of time inherited by subsequent driver parking in a space with time left on a meter from a previous parking event
16	Time of surveillance	Time when parking enforcement passed by
17	Citation issued during observation	Indicate whether any parking citations were issued during the parking event
18	Notes	Notes
19	Reason for "did not record" if applicable	Notes regarding any information not observed and/or recorded

3.3.1 Sampling Strategy

To select a sample of block faces and time periods during the day for the field study, we calculated the average occupancy rate from the secondary meter transaction data for parking meters ("poles") in our study area. We used the parking occupancy rate from the secondary meter transaction data to achieve two goals in our sampling strategy: 1) select a sample of block faces in the study area that represents variations in parking occupancy across the study area; and 2) select periods during the day that represent differences in parking patterns during peak versus off-peak hours across the study area. The sampling strategy included four steps: selecting block faces, selecting hours, assigning block faces to different observation hours, and assigning block faces to different days during the week.

Initially, we calculated the average occupancy rate of parking meters (poles) from 8:00 a.m. to 5:00 p.m. to know the range of occupancy rates at poles. The occupancy rate for any individual pole varies from 36% to 96% during that time period (Figure 3.2). There is also variation in parking occupancy rates by block (*subarea*) within the study area (Figure 3.3). The sampling strategy would need to capture this variance.

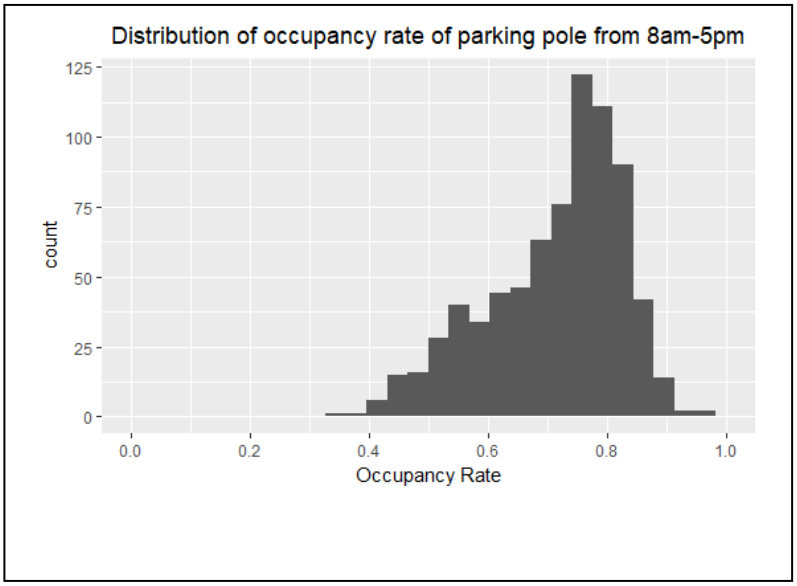


Figure 3.2 Average occupancy rate of poles in the study area, Denver municipal parking data

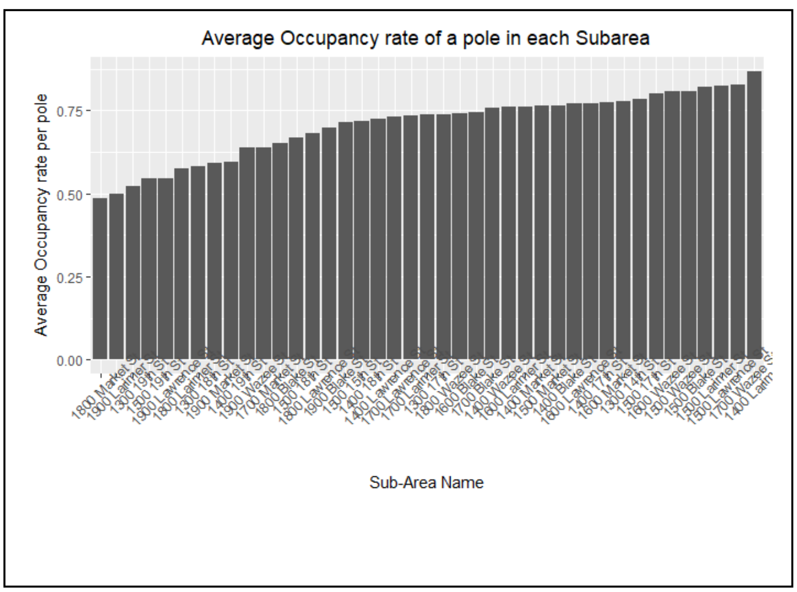


Figure 3.3 Average occupancy rate of poles by block, Denver municipal parking data

We first randomly selected 10 block faces from each quartile of block faces in the occupancy rate distribution among the 74 block faces, totaling 40 block faces as our target for data collection. 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 thus were unavailable for parking, for instance, in construction zones.

Next, we graphed the hourly occupancy rate of meters for each quartile of the 40 block faces in the sample, again based on the secondary meter transaction data from the City of Denver, to observe the fluctuation in occupancy rate with time during the day (Figure 3.4). Visually, all four graphs indicate roughly two peak time periods, 11:00 a.m.–2:00 p.m. and 5:00 p.m.–8:00 p.m., where the occupancy is comparatively high. In addition, they indicate an off-peak time period 8:00 a.m.–11:00 a.m., where the occupancy is comparatively low. Therefore, we decided to include 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 our field study. The two peak time periods also allowed us to include parking events with potentially different purposes, with the 11:00 a.m.–2:00 p.m. period potentially representing more business-related travel and parking events, and the 5:00 p.m.–8:00 p.m. period potentially representing more consumer-related travel and parking events (shopping and dining).

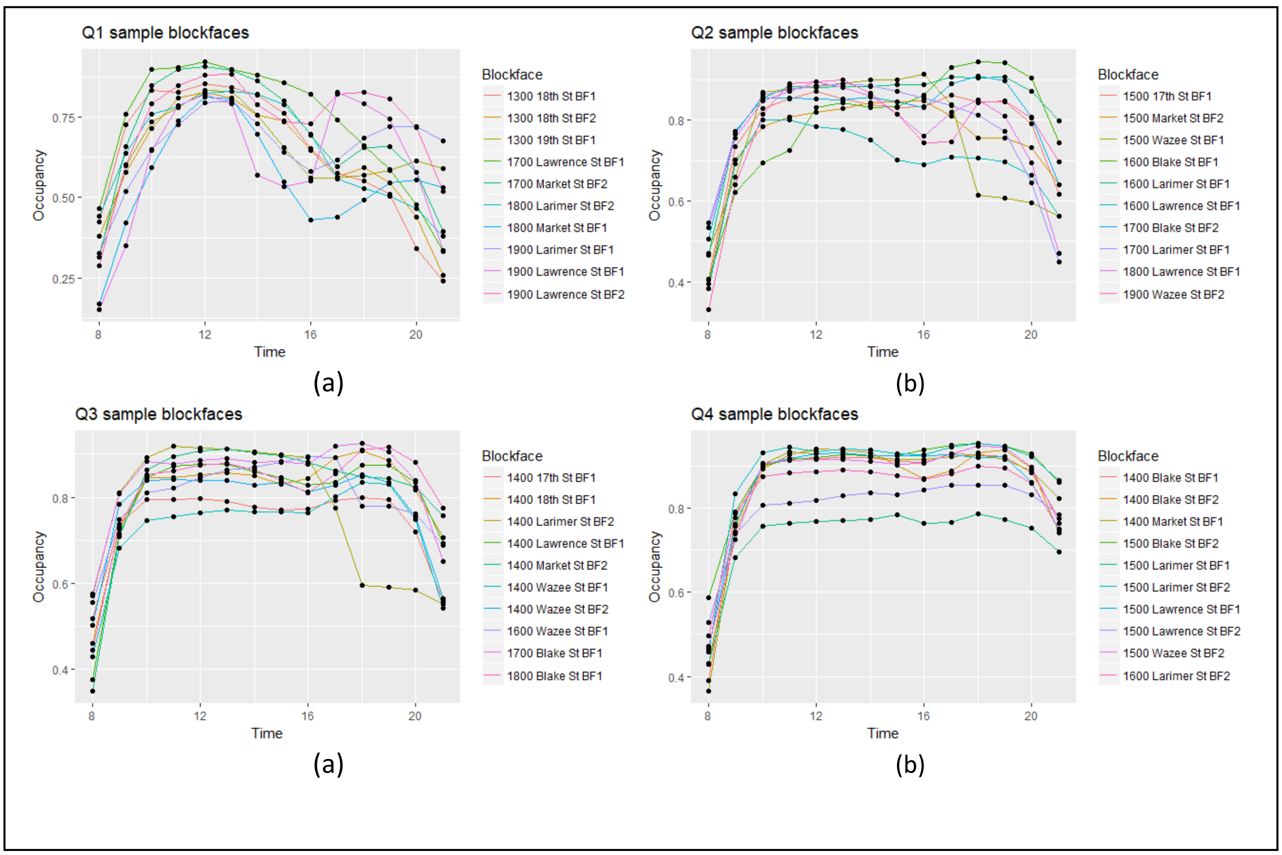


Figure 3.4 Hourly average occupancy rate of poles by block face, Denver municipal parking data

Subsequently, within each quartile (10 out of the 40 block faces in the sample), we assigned four block faces for observations during 8:00 a.m.–11:00 a.m., three block faces for observations during 11:00 a.m.–2:00 p.m., and three block faces for observations during 5:00 p.m.–8:00 p.m. Table 3.3 provides details about the block faces selected and the times they were assigned for observation.

Finally, each of the selected 40 sample block faces was randomly allocated to one of the five weekdays to remove any variation of parking behavior based on the day of the week, as detailed in Table 3.4. Three block faces were not observed due to logistical issues, or the parking meters being covered after the sampling strategy was determined (1400 17th St. BF1, 1500 Larimer St. BF 1 & 1700 Blake St. BF2). Thus, only 37 block faces that we initially planned in the sampling strategy were included in this study.

The data collection occurred during a three-week period from April 2–April 20, 2018. Each block face was always observed on the day of the week as assigned but could be observed on any week of the three-week period. All parking events during the same observation session were always recorded by the same research assistant out of five total research assistants.

Note that we also conducted a pilot test from February 28–March 13, 2018, on five block faces in the study area for two-hour periods each, which occurred before finalizing the sampling strategy and determining the block faces to include in the field study. 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 these five block faces we observed in the pilot study ended up being sampled again in our field study based on the sampling strategy. The pilot study led us to shift from two hours to three hours for each observation period in the field study. To maximize sample size, we decided to include the pilot data in the final dataset along with data collected during the official field study.

In summary, the dataset from the field study included parking events observed in three-hour periods from each of the 37 block faces based on the sampling strategy, as well as parking events observed in two-hour periods from each of five block faces from the pilot study.

Table 3.3 Block faces included in the field study sample and their observation times

	8:00 a.m. to 11:00 a.m.	**11:00 a.m. to 2:00 p.m.**	**5:00 p.m. to 8:00 p.m.**
Q1	1800 Market St BF1	1900 Larimer St BF1	1700 Lawrence St BF1
	1900 Lawrence St BF1	1700 Market St BF2	1300 18th St BF1
	1900 Lawrence St BF2	1800 Larimer St BF2	1300 18th St BF2
	1300 19th St BF1		
Q2	1700 Blake St BF2	1600 Larimer St BF1	1800 Lawrence St BF1
	1600 Blake St BF1	1500 Market St BF2	1600 Lawrence St BF1
	1500 17th St BF1	1500 Wazee St BF1	1900 Wazee St BF2
	1700 Larimer St BF1		
Q3	1800 Blake St BF1	1400 17th St BF1	1400 Lawrence St BF1
	1600 Wazee St BF1	1400 Wazee St BF1	1400 18th St BF1
	1400 Larimer St BF2	1400 Wazee St BF2	1400 Market St BF2
	1700 Blake St BF1		
Q4	1500 Blake St BF2	1400 Blake St BF2	1500 Larimer St BF2
	1600 Larimer St BF2	1400 Market St BF1	1500 Wazee St BF2
	1500 Larimer St BF1	1500 Lawrence St BF2	1400 Blake St BF1
	1500 Lawrence St BF1		

Table 3.4 Assignment of sampled block faces to observation periods

	Monday	Tuesday	Wednesday	Thursday	Friday
8am-11am	1800 Market St BF1 1300 19th St BF1	1900 Lawrence St BF1 1400 Larimer St BF2 1600 Wazee St BF1 1600 Blake St BF1	1700 Blake St BF1 1500 17th St BF1 1600 Larimer St BF2 1500 Lawrence St BF1	1700 Larimer St BF1 1500 Blake St BF2	1800 Blake St BF1 1500 Larimer St BF1 1900 Lawrence St BF2
11am -2pm	1400 Blake St BF2	1500 Wazee St BF1 1400 Wazee St BF1		1700 Market St BF2 1800 Larimer St BF2 1400 Wazee St BF2	1900 Larimer St BF1 1600 Larimer St BF1 1500 Market St BF2 1400 17th St BF1 1400 Market St BF1 1500 Lawrence St BF2
5pm-8pm	1800 Lawrence St BF1 1400 Lawrence St BF1	1700 Lawrence St BF1 1500 Wazee St BF2 1600 Lawrence St BF1	1300 18th St BF2 1900 Wazee St BF2 1400 Market St BF2 1400 Blake St BF1	1400 18th St BF1 1500 Larimer St BF2	1300 18th St BF1

3.3.2 Data Collection Procedures

The field data collection procedure involved developing a field study protocol and data collection instrument, testing, and refining the protocol and instrument, and training students to use the protocol and instrument to collect complete and accurate field data. The data collection protocol and the instrument are included in the appendices.

Key points for field data collection included:

1. We do not collect identifying information about travelers or vehicles. Our unit of observation is the parking event at a parking meter, not a person.
2. We seek complete information about each observed parking event on each block face for each study period.
3. Students who collect field data are trained and supervised by faculty members (principal investigators) to be safe and aware while in the field.

Field data collectors debriefed with the graduate student supervisor after each observation session (i.e., daily) and we held weekly team meetings to discuss the data collection process. All students were encouraged to express difficulties and challenges as they arose so that we could solve problems and ensure we would minimize errors. Students carried cell phones to make emergency calls and to ask questions and clarify procedures, if necessary. We did not receive any emergency calls or clarifying questions directly from the field.

Students were assigned block faces and were given a map of the study area to be observed during each session, as well as the data collection instrument. Upon arriving at the site, students confirmed that each of the parking meters was functioning (poles and their numbers) and recorded the baseline data for each meter (time on meter, vehicle description of any parked vehicles, any citations). After completing the census of the existing parking events, students observed each arrival and departure of all vehicles on the block face, noting the appropriate data in the instrument.

Each data collection instrument was turned in after the field session, scanned, and then the data were entered into a spreadsheet for further analysis.

3.4 Analytical Approach

The field study 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.

Because our observations in the field study captured only a three-hour period each time (and two hours in the pilot data), 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 significant bias by focusing on relatively shorter parking events, because longer parking events may have been removed due to arrival time before the observation period started or departure time 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 from the City of Denver (2015–2016) that we used for the imputation 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. Because drivers usually pay for the meter within a few minutes after arrival, meter payment time from the secondary dataset is a relatively 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 the field study, our main analysis used a subset of 567 parking events where the departure time was 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 dataset from the City of Denver from October 2015–September 2016 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 a.m., 11 a.m., or 5 p.m. (the beginning of the three time periods of data collection in Study 1) on any day between October 2015–September 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 time. For example, assume we observed a parking event in the 11 a.m.–2 p.m. study session in April 2018 in Study 1 at a particular block face, and this parking event had a missing arrival time. To start the imputation, we first identified a population of parking events in the meter transaction dataset at this block face where the parking meter had paid time on it at 11 a.m. (indicating a vehicle already parked here prior to 11 a.m.) on any day from October 2015 to September 2016.

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 minutes of the departure time of the parking event we observed and are trying to impute for, 2) the parking record in the secondary dataset had a meter payment time that was earlier than the beginning of the field observation session for the parking event we are trying to impute (and therefore would represent an arrival time that would not have been observed during the study session). Records that satisfy these two conditions represent potential parking events that, if they occurred in 2018, would represent a collection of parking events that arrived before the study session, resulting in missing arrival time, but departed at a time similar to the vehicles we observed in the field with missing arrival time.

Based on the records that satisfied these criteria, we constructed a cumulative distribution function of the time of meter payment (as a proxy for arrival time). We drew five random data points from this distribution function and took the mean to use 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. That is, the analysis did not include parking events where the vehicle departed after the observation. 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 dataset 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. It is worth noting that for the case of unobserved (imputed) arrivals, we cannot determine whether the drivers paid the meter out of pocket or inherited payment from previous drivers, because we did not observe the arrival and the status of the meter at the time of arrival. This distinction leads to different sample sizes used in certain calculations of occupancy-related rates, depending on whether the metric of interest requires knowledge of the payment status of a parking event.

4. RESULTS

4.1 Summary Statistics of Parking Events

In the following sections we present information for each of the indicators measured during the field observation, including the duration of parking events, inherited time, underpayment and overpayment, paid time, and the difference between the actual arrival time of the vehicle and the time of payment. Table 4.1 presents summary statistics and Figure 4.1 presents a flow chart summarizing the various events.

Table 4.1 Summary of observed parking events

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

Note: (*) These include imputed values from arrivals simulations.

Time inheritance status	Driver out of pocket payment status	Number of parking events with over, under, or exact payment			Mean parking duration in min (SD)	Mean paid time in minutes (SD)	
		Over-paid	Under-paid	Exact payment		Driver paid time	Inherited time
Driver inherited time (n = 114)	Driver paid out of pocket (n = 56)	49	5	2	52.14 (35.40)	61.34 (35.36)	23.14 (21.88)
	Driver did not pay out of pocket (n = 56)	36	18	2	18.41 (20.95)	0	27.50 (20.08)
	Driver payment status unknown (n = 2)	Unknown					
Driver did not inherit time (n = 238)	Driver paid out of pocket (n = 151)	111	37	3	73.85 (49.19)	80.03 (37.98)	0
	Driver did not pay out of pocket (n = 82)	0	80	2	27.59 (42.72)	0	0
	Driver payment status unknown (n = 5)	Unknown					
Time inheritance unknown (n = 215)	Driver paid out of pocket (n = 70)	59	10	1	77.51 (46.67)	61.34 (35.36)	unknown
	Driver did not pay out of pocket (n = 21, including 15 payment accuracy unknown)	0	5	1	6.10 (562)	0	unknown
	Driver payment status unknown (n=74)	36	36	2	102.50 (23.13)	unknown	unknown
	Meter reading not recorded (n=50)	unknown	unknown	unknown	100.1 (30.65)	unknown	unknown

Figure 4.1 Inherited time, paid time, and parking overpayment and underpayment

4.1.1 Duration of Parking Events

Our field observation period lasted three hours (and two hours in data from the pilot study). Most block faces had a maximum parking time limit of two hours, but one block face had a maximum time limit of three hours. To account for arrivals and departures that we did not directly observe, we imputed the missed arrival times using secondary parking transaction data from 2015–2016 provided by the City of Denver as described above.

Table 4.1 and Figure 4.2 show the distribution of parking durations in the sample of 567 parking events used in the analysis. The duration of observed parking events ranged from 0 minutes to 195.60 minutes, with a mean of 63.10 minutes and median of 62.00 minutes, respectively, whereas one-quarter of parking events were under 12.50 minutes and three-fourths of parking events were equal to or less than 103.60 minutes.

Field observers noted that shorter parking events can include drivers dropping off passengers, picking up passengers, parking but not exiting the vehicle, and staying in the vehicle as they waited for passengers to go out and return, etc. Table 4.1 also shows that 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 minutes, $t(110) = 6.14$, $p < .001$) and when they did not inherit time ($M = 27.59$ vs. 73.85 minutes, $t(231) = 7.17$, $p < .001$).

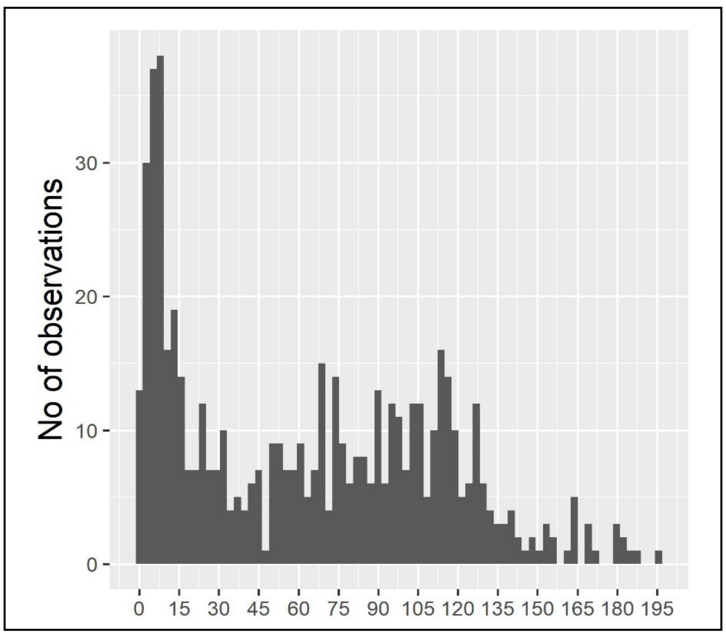
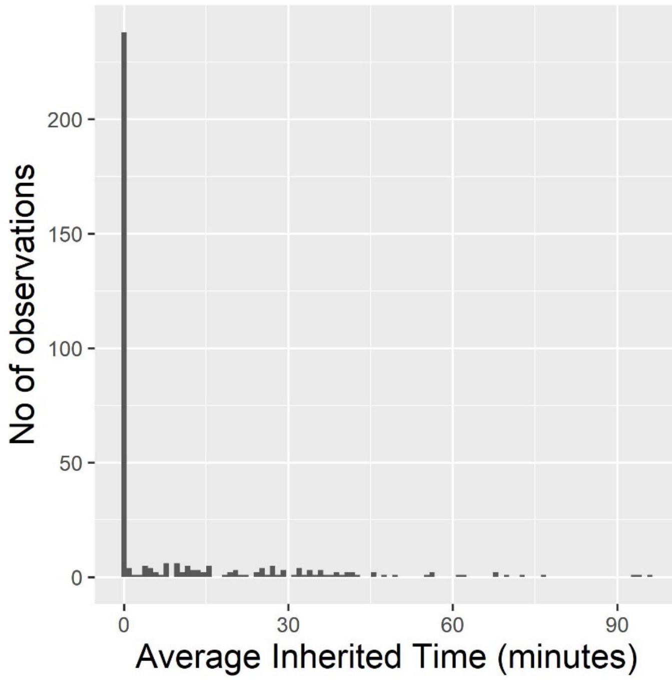


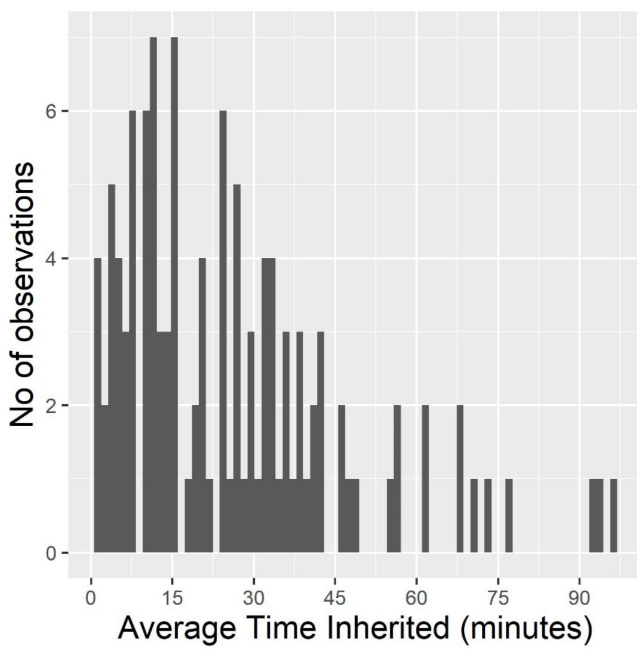
Figure 4.2 Distribution of parking event durations N=567

4.1.2 Inherited Time and Inter-user Transfers

Of the 567 parking events observed in our field study, 114 parking events (20%) involved inherited time from a previous driver at the same meter (Figures 4.1 and 4.3). Of those who inherited time, the mean time inherited was 26.22 minutes (Table 4.1). Averaging this over the entire population of parking events for which we have information about inherited time (N=352), the mean inherited time per parking event is 8.49 minutes.



(a)



(b)

Figure 4.3 Distribution of inherited time

The mean inherited time among those who inherited time (N=114) was 26.22 minutes. We also know that 56 (49%) drivers who inherited time did not put additional payment in the meter and 56 (49%) did pay the meter out of pocket (Figure 4.1). Those who inherited time and paid the meter out of pocket had longer parking durations (52.14 minutes) than those who did not pay out of pocket (18.41 minutes), though both groups inherited about the same amount of time (23.14 and 27.50 minutes, respectively). Among the 56 drivers who inherited time and did not pay the meter out of pocket, 36 had more than enough inherited time to cover the entire cost of their stay, 18 stayed longer than the duration paid for with inherited time, and two inherited exactly the right amount.

There are 215 events for which were unable to determine whether the driver inherited time. This includes the 192 imputed arrivals (i.e., unobserved arrivals) plus 23 additional events in the field that we did observe. These 23 events represent heterogenous conditions. Upon the arrival of these 23 vehicles, we watched the drivers from a distance to see whether they paid the meter. In certain cases, drivers passed time in the car before exiting to pay; in other cases, the drivers dwelled in the parking space before driving away. In these situations, if we had not recorded remaining time from the previous driver, or if the event happened before the start of our observation period, then we did not know whether the driver inherited time. For these events where driver inheritance is unknown, for those that we observed we do know for certain whether the driver paid the meter out of pocket or not.

4.1.3 Underpayment and Overpayment

We define *underpayment* as a parking event where the vehicle occupies the parking space after the meter expired. Note that for simplicity, this definition did not include the rare cases of underpayment that occurred in the beginning or middle of the parking duration (e.g., there were six parking events where the meter was expired for a period of time after the first payment expired and before the second payment occurred). Based on this definition, of the 567 parking events, N=191 (34%) were underpaid (Table 4.1 and Figure 4.4). The distribution of underpayment is highly skewed. Most of the vehicles with underpayment remained only a short time past their meter's expired time. The median underpayment was for 9.00 minutes, the mean was 19.38 minutes, and the maximum was 162.00 minutes.

We define *overpayment* as a parking event where the vehicle leaves a parking space before the meter expired. In this study, N=291 (51%) of parking events were overpaid (Table 4.1, Figure 4.1, Figure 4.5). Of the parking events that were overpaid, the mean overpayment time was 30.68 minutes. More than half of the observed users overpaid the meter by 25 minutes or more.

We observed 11 drivers who left the parking space right at the time the meter expired. These exact payments represent a negligible number of events. Additionally, two drivers parked at the meter for less than one minute and did not pay, which we also consider as having perfect payment. Together, these 13 observations of "perfect payment" constituted 2% of the 567 parking events in the analysis.

Note that payment accuracy status was unknown for 72 (13%) parking events due to missing information on payment status and amount, or both.

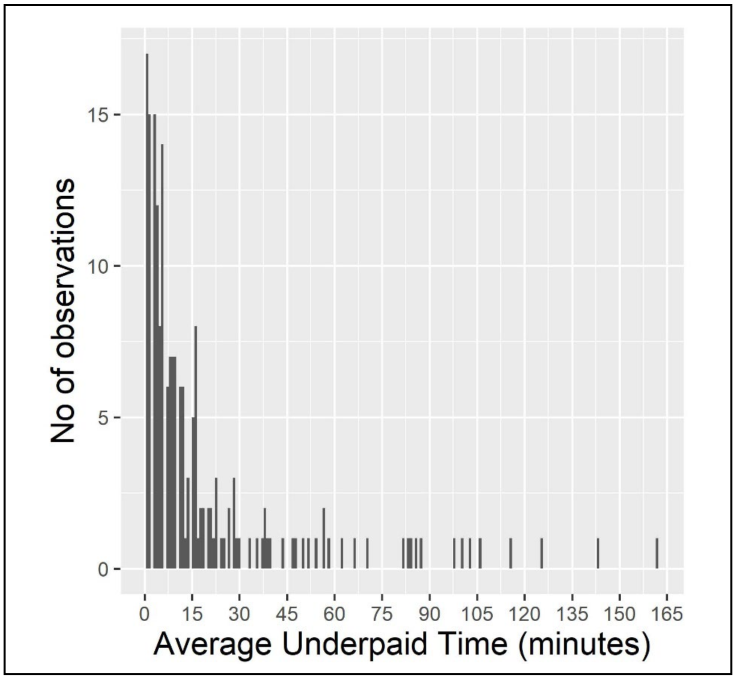


Figure 4.4 Distribution of underpaid parking observations (N=191)

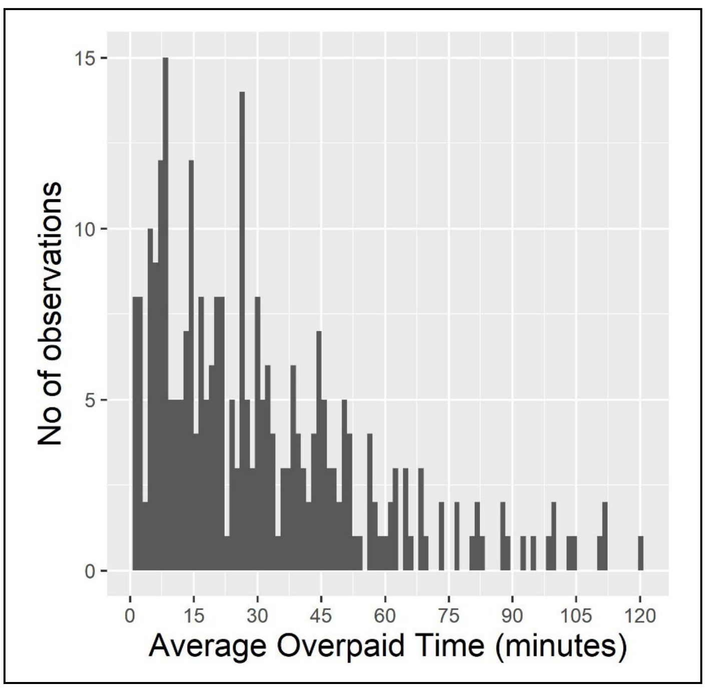


Figure 4.5 Distribution of overpaid parking observations (N=291)

4.1.4 Time Paid Out of Pocket

The total time paid out of pocket by drivers (N=277) ranged from 5 to 208 minutes with a mean of 79.92 minutes and a median of 76.00 minutes (Table 4.1). Among drivers who paid a non-zero amount out of pocket, they most commonly paid for 15, 30, 60, or 120 minutes of parking (Figure 4.6). The distribution is similar when accounting for inherited time. The total paid time (out of pocket by the driver plus inherited time) ranged from 0 to 208 minutes and had a mean of 57.24 minutes and a median of 59.00 minutes (Table 4.1; Figure 4.7). Of the N=159 who did not pay for time out of pocket, 56 had inherited time (Figure 4.1).

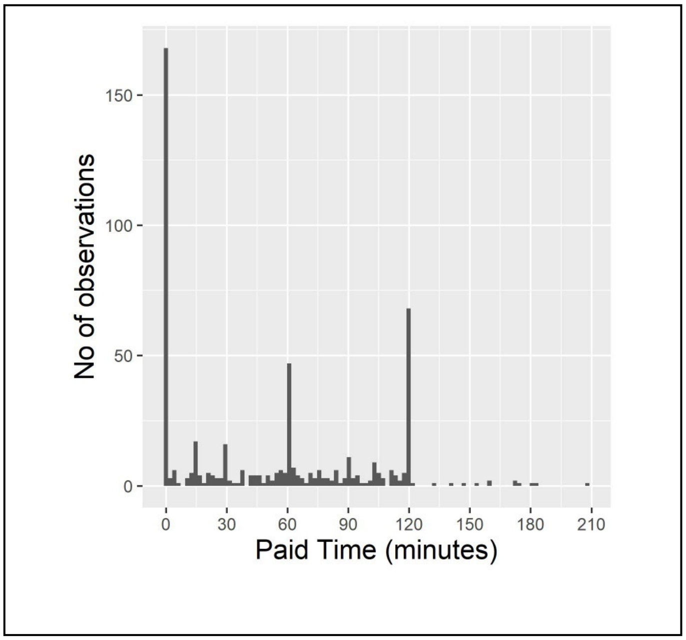


Figure 4.6 Distribution of time paid out of pocket per parking event (excluding inherited time, N=515)

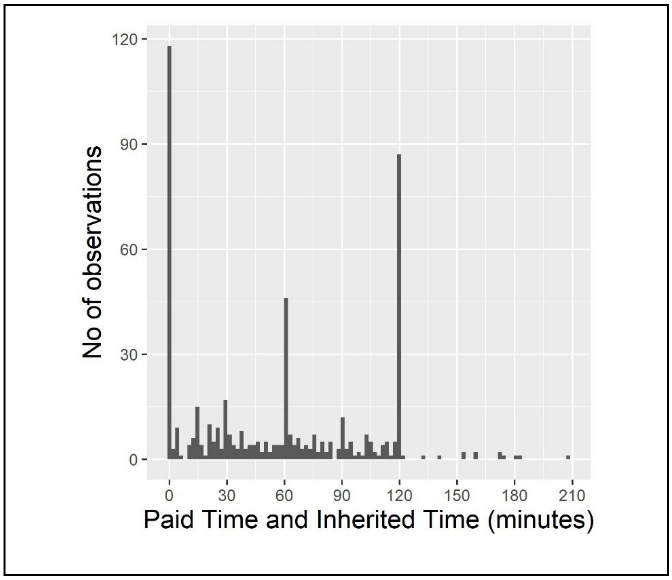


Figure 4.7 Distribution of total time paid per parking event (out of pocket and inherited, N=515)

The amount that drivers paid out of pocket for their total occupancy, including people who did not pay at all, ranged from $0.00 to $3.47 with a mean of $1.33 and median of $1.27 (Figure 4.8). When accounting for inherited time, the total paid time (paid out of pocket by the driver plus what remained from the previous driver), and drivers who did not pay at all, the total payment ranged from $0.00 to $3.20 with a mean of $0.28 and median of $0.00 (Figure 4.9).

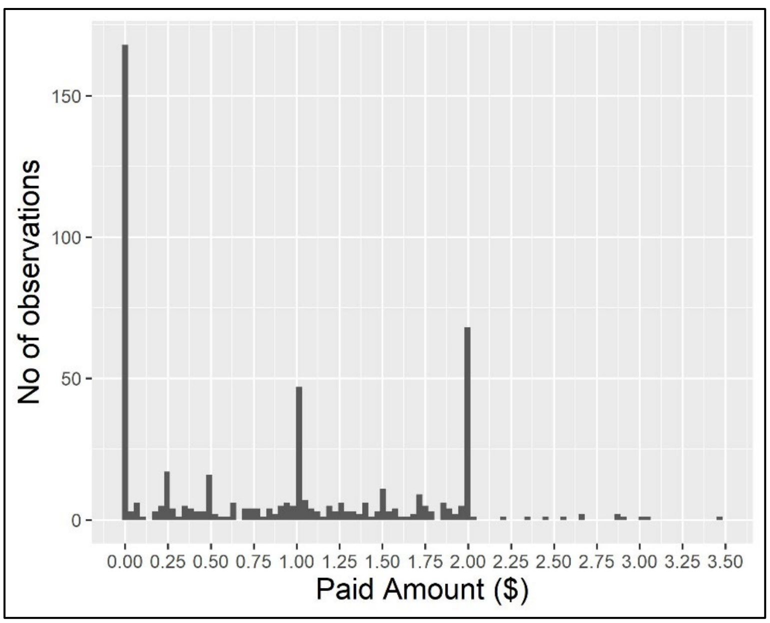


Figure 4.8 Distribution of amount paid out of pocket per parking event

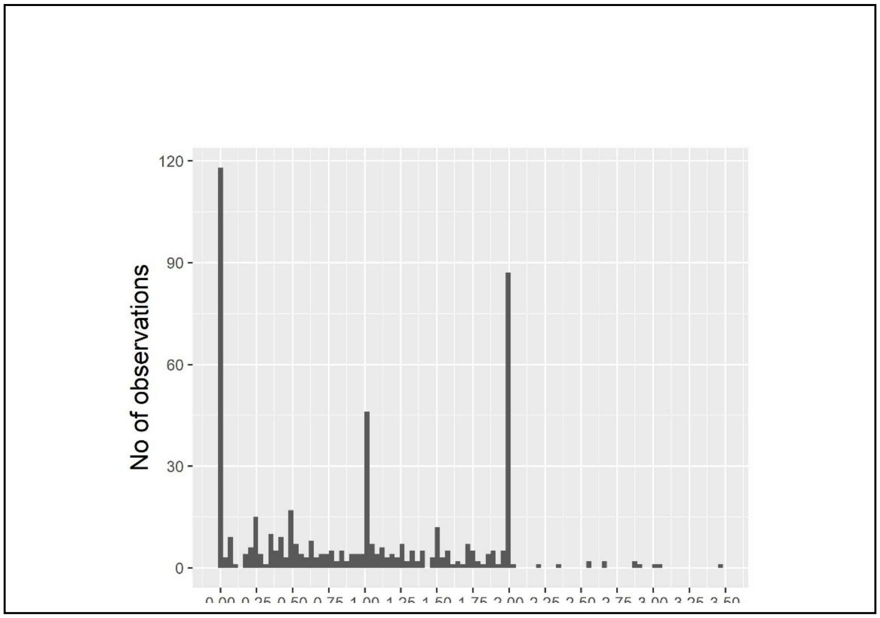


Figure 4.9 Distribution of total amount inherited and paid out of pocket per parking event

During the field observation we noticed a difference between the arrival time of the vehicle and time when the meter was paid. While most of the drivers took less than five minutes to pay the meter from the time of arrival, drivers took as long as 53 minutes before paying the meter (Figure 4.10).

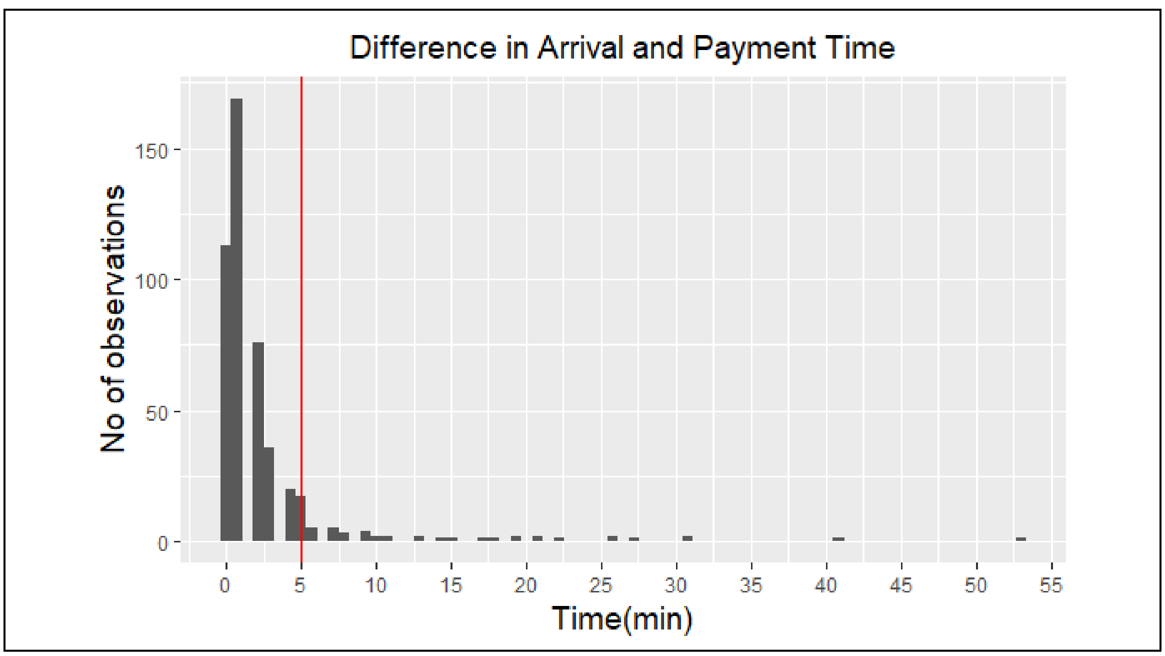


Figure 4.10 Distribution of the difference between vehicle arrival time and meter payment time N=375

4.2 Parking Events from a System Perspective

Most parking events in this study, N=291 or 66% of the events for which we have payment information, were overpaid, resulting in donated time to the system. That time was either transferred to other users (32% of drivers who inherited time, for cases with information on inherited time) or transferred to the city. In fact, the drivers who technically overpaid may have inherited some of the time that covered their occupancy, such that they would not have incurred a personal loss of payment.

We observed 11 drivers who left as soon as the meter expired. Among these "exact" payments, four inherited time, five did not inherit time, and two were cases without information about inheritance. These exact payments represent a negligible number of events.

Figure 4.11 shows the distribution of overpayment, underpayment, and exact payment events based on the time on the meter post departure. Note that this is not a perfectly accurate representation of overpayment and underpayment because we imputed some values using meter transaction data, and therefore we have assumed that the start of the parking event is the time of payment, which was usually not the case. In the field, the payment time lagged behind the arrival time (Figure 4.10).

In the figure, values in green indicate that a vehicle departed before the meter expired (i.e., it departed while there was still some time left on the meter); these positive values show overpayments to the system. Negative time on the meter, or values in blue, represent vehicles that occupied the parking space beyond their meter's expiration time, which are underpayments to the system. It should be noted that the actual meter does not show negative time values but shows that the meter has expired. We have computed this value as "negative values" for the ease of understanding.

The distribution presented in Figure 4.11 indicates there are more overpayments to meters than underpayments. Lower skewness of the overpayments compared with higher skewness of the underpayments shows that drivers tend to overpay a higher amount.

When we also consider parking events that were not paid for at all, the net endowment is negative. Across the system, any given parking event recovers only about 81% of the expected revenue for its occupied time (see section 4.3). Nevertheless, drivers who overpay subsidize those who overstay or do not pay at all.

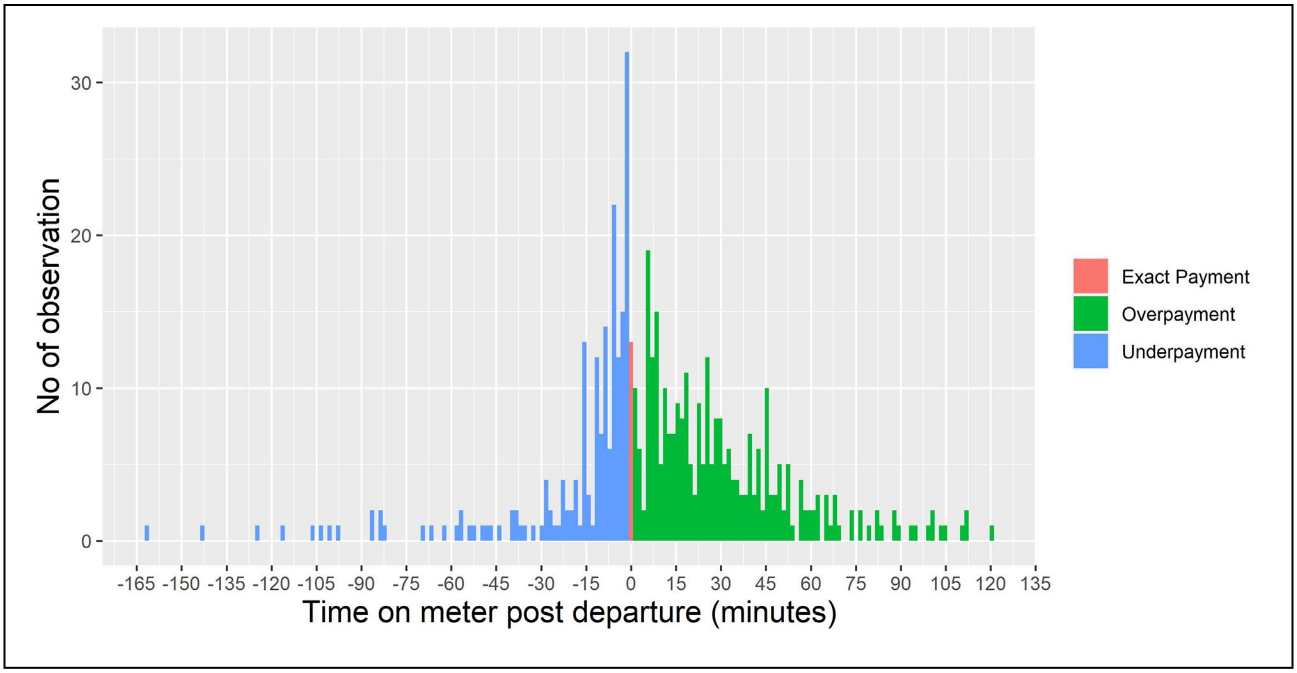


Figure 4.11 Distribution of overpayment and underpayment, N=567

4.3 Payment Compliance

We define *payment compliance* as paying for the parking that one consumes. Perfect payment compliance is when:

$$Total\ paid\ and\ occupied\ time\ /\ occupied\ time\ =\ 1.$$

The payment compliance rate cannot be greater than 1 and it counts the time that drivers pay out of pocket as well as inherited time. The observed payment compliance rate in the study was 0.8183 (Table 4.2). On average, users did not pay for all of the parking they consumed, despite the inter-user transfer, because some users did not pay at all.

The payment compliance rate does not reflect cases where drivers overpaid the meter. We considered three additional metrics, presented in Table 4.2, that represent the ratio of payment to occupancy, which does capture these cases of overpayment and disaggregates them by the source of the payment. The payment-to-occupancy ratio was 1.5515. This metric can decompose into two parts, the out-of-pocket payment-to-occupancy ratio, which was 1.15859, and the inherited payment-to-occupancy ratio, which was 0.69334.

Table 4.2 Observed payment compliance rates by parking event

	Metric	Description	N	Rate per parking event
1	Payment compliance rate	The ratio of the paid-occupied time to the total occupied time of a parking event. Driver overpayment is excluded.	563	0.8183
2	Payment-occupancy ratio	The ratio of total paid time (can be more than paid-occupied) to occupied time, per event.	500	1.5513
3	Out-of-pocket payment- occupancy ratio	The ratio of driver paid out-of-pocket time to occupied time, per event.	460	1.15859
4	Inherited payment-occupancy ratio	The ratio of inherited time to occupied time, per event.	350	0.6934

4.4 Occupancy

Table 4.3 presents occupancy rates by payment status by pole and Figure 4.12 presents the frequency distributions for the metrics across poles in the study area. These calculations are based on field observations without imputation because we consider the time that parking spaces are left vacant. This biases the analysis toward shorter events, which may not represent the full range of parking behavior. This table presents metrics based on total paid time, which is the sum of time paid out of pocket by the driver and time inherited; that is, all paid time regardless of the source. On average, per parking meter (pole), 41.73% of the total observed time (*study time*) was paid and occupied, and another 8.69% of total observed time was occupied but not paid for. Overall, the average occupancy rate was 50.42% for the observation period. The complement metric, the vacancy rate, was 49.585% by pole; 7.945% of the study time was paid for but unoccupied.

Table 4.3 Summary of occupancy rates by payment status

	Pole mean	Min	1st	Med	Mean	3rd	Max
$\frac{Total\ paid\ occupied\ time}{Study\ time}$	41.73%	0.00	0.1611	0.4472	0.4173	0.6604	1.00
$\frac{Unpaid\ occupied\ time}{Study\ time}$	8.69%	0.00	0.00	0.01667	0.08691	0.08333	0.09000
$\frac{Total\ paid\ vacant\ time}{Study\ time}$	7.95%	0.00	0.00	0.03611	0.07945	0.13333	0.38333
$\frac{Unpaid\ vacant\ time}{Study\ time}$	41.64%	0.00	0.1757	0.333	0.4164	0.6431	0.9944

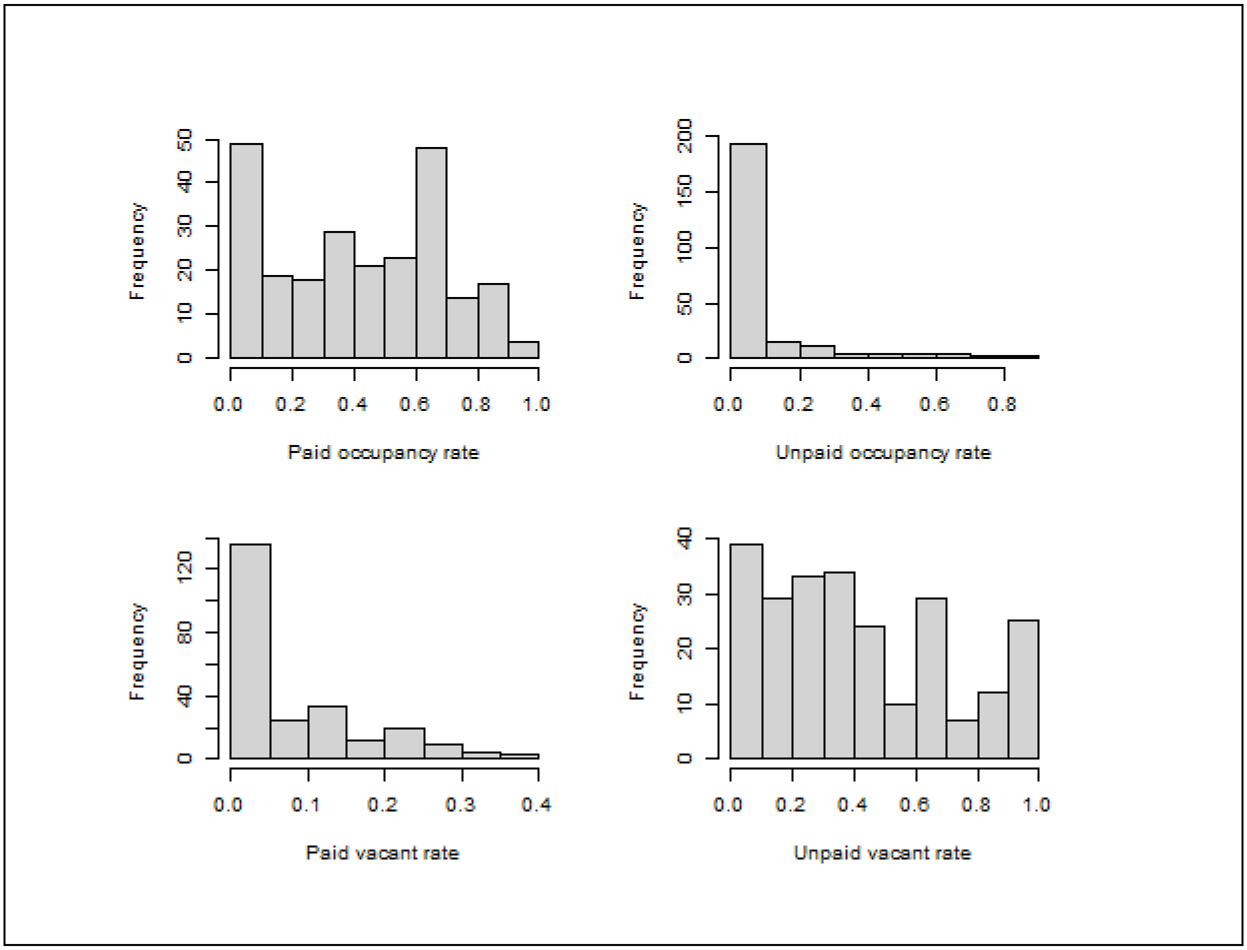


Figure 4.12 Distributions of occupancy rates by payment status

The distribution of the occupancy rates reflects differences in demand across the study area. Focusing on the third quartile shows that 25% of the poles in the study area had occupancy rates higher than 74%, which would be considered high-demand areas suitable for implementing demand-based pricing strategies.

To compute the rates, we excluded 72 observations for which we did not have a record of the meter expiration time due to experimental error, which resulted in the full exclusion of 65 poles from this section of the analysis (there were N=747 poles in the study area).

5. DISCUSSION

The current research found that 98% of consumers either underpay or overpay the parking meter. In addition, 32% of drivers inherited time from a previous driver. Thus, in an overwhelming majority of parking events, actual payment deviates from the set parking price. The degree of deviations is also not trivial, averaging at about 20 minutes of unpaid parking for those who underpaid, and about 30 minutes of extra unused parking fees for those who overpaid.

To see the financial impact of payment inaccuracy, we scaled up the proportion of underpayment and overpayment we observed. 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, which is 1,683,013 parking events. Given that we 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 expose drivers to the risk of a $25 to $50 fine each time, while at the same time owing a total of $209,758 to the city. Echoing the INRIX data we cited at the beginning of this report, this vast 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 and unwise for the system to punish drivers for inaccurate payment. The existing parking system uses punishment—citations—to deter drivers from underpaying for parking, with the underlying assumption that underpayments are intentional. Our results, however, point to the opposite conclusion. Our data suggest that parking payment inaccuracy is virtually omnipresent. Drivers are mostly trying diligently to pay the right price, but we still make mistakes almost all the time, suggesting that accurate payment is virtually impossible to accomplish despite good intentions. Thus, it is unfair to punish drivers for payment mistakes they did not intend to make and cannot possibly avoid even if they tried. The system needs to recognize that they are placing an unrealistic expectation of human perfection on drivers.

Second, and more importantly, payment inaccuracy can severely mask price variations, which are critical for the efficacy of parking systems that use dynamic pricing to influence 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. Given the $0.33–$0.50 of payment inaccuracies that we have observed drivers experience every time they park, the $0.25/hour price variation could be easily drowned out by the noise of payment imprecisions and failure to incentivize drivers' behavior. This calculation likely underestimates payment inaccuracy in San Francisco. The per-hour parking price is lower in Denver than in San Francisco, and assuming the same overpaid or underpaid duration in parking events in both cities, the payment inaccuracy is likely larger in dollar amounts 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 simply too large to ignore.

The solution we propose is an automatic, duration-based parking payment system. This system will erase the problem of payment imprecision for metered parking, and thus solve the problem of unfair financial burden to drivers, as well as the problem of drowned out price signals in dynamic meter pricing. In addition, automatic, duration-based parking payment prepares cities for the future. With increasing vehicle automation, a duration-based automatic payment system will prepare cities for an adaptive, smart, and connected transportation system.

The problem of parking payment inaccuracy is serious, the solution is ready, and the public supports it. We just need the will to act. Our recommendation to cities across America: Abandon the current system of parking meters and meter policing and replace them with automatic parking payments based on actual parking durations.

6. CONCLUSIONS

In this study we have used behavioral insights to reframe parking payment as an unrealistic and unfair system in which people are expected to pay the exact right amount for parking, which is nearly impossible. The use of deterrence in this context is unjustified. Furthermore, the expectation that pricing on-street parking meters can manage demand is based on faulty assumptions of rational decision making. Instead, parking systems should use available technology to switch to an automatic system that eliminates the need for drivers to estimate their parking duration. In this scenario, parking pricing would be fairer and better equipped to manage parking demand.

7. WORKS CITED

Adams, Caroline, and Paul Webley. (1997). "The role of economic and psychological variables in parking violations." *Psychology, Crime and Law*, 3(2), 111-133.

Ariely, Dan. (2008). *Predictably Irrational*. New York: HarperCollins.

Arnott, Richard. (2014). "On the optimal target curbside parking occupancy rate." *Economics of Transportation*, 3(2), 133-144.

Barracho Oliveira, and Ana Lúcia. (2016). "A gestão do estacionamento irregular em zonas urbanas críticas da cidade de Lisboa." (Doctoral dissertation).

Black, Ian, Kevin Cullinane, and Chris Wright. (1993a). "Parking enforcement policy assessment using an economic approach: Part 1: Theoretical background and the development of an economic model." *Transportation Planning and Technology*, 17(3), 249-257.

City of Charleston, South Carolina. (2018). https://charleston-sc.gov/DocumentCenter/View/34

City of Sacramento, California. (2018).

http://www.cityofsacramento.org/Public-Works/Parking-Services/Street-Parking/Meters/Rates

Cope, John G., Linda J. Allred, and Joseph M. Morsell. (1991). "Signs as deterrents of illegal parking in spaces designated for individuals with physical disabilities." *Journal of Applied Behavior Analysis*, 24(1), 59-63.

Cullinane, Kevin. (1993). "An aggregate dynamic model of the parking compliance decision." *International Journal of Transport Economics/Rivista internazionale di economia dei trasporti,* 20(1), 27-50.

Gibbs, Jack P. (1986). "Deterrence Theory and Research. The law as a behavioral instrument." Gary B. Melton, ed., Nebraska Symposium on Motivation, 33, 87-130.

Horst W. J. Rittel, and Webber, M. (1973). "Dilemmas in a General Theory of Planning." *Policy Sciences*, 4(2), 155-169.

Inci, Eren. (2015). "A review of the economics of parking." *Economics of Transportation*, 4(1), 50- 63.

Kahneman, Daniel. (2003). "Maps of Bounded Rationality: Psychology for Behavioral Economics." *The American Economic Review*, 93(5), 1449-1475.

Keenan, Edward. (2010). "Prize-winning innovators Skymeter could revolutionize parking – and eliminate traffic." Yonge Street. http://www.yongestreetmedia.ca/innovationnews/skymeter0602.aspx

Kerley, Richard. (2007). "Controlling urban car parking – an exemplar for public management?" *International Journal of Public Sector Management*, Vol. 20 Issue: 6, pp.519-530

Kogut Tehela, and Ritov Ilana. (2011). “The identifiable victim effect: causes and boundary conditions.” In: Oppenheimer D.M., Olivola C.Y., (eds.) *The Science of Giving: Experimental Approaches to the Study of Charity*. New York: Taylor and Francis.

Lei, Chao, Qian Zhang, and Yanfeng Ouyang. (2017). “Planning of parking enforcement patrol considering drivers’ parking payment behavior.” *Transportation Research Part B*, 106, 375–392.

Morillo, Carlos, and José Magín Campos. (2014). “On-street illegal parking costs in urban areas.” *Procedia-Social and Behavioral Sciences*, 160, 342-351.

Petiot, Romain. (2004). “Parking enforcement and travel demand management.” *Transport Policy*, 11(4), 399-411.

Rothengatter, Talib. (1982). “The effects of police surveillance and law enforcement on driver behaviour.” *Current Psychological Reviews*, 2(3), 349-358.

Sadhukhan, Pampa. (2017). “An Iot-based E-parking system for smart cities.” School of Mobile Computing & Communication Jadavpur University Kolkata, India.

San Francisco Municipal Transportation Agency (SFMTA). (2014). SFpark: Pilot Project Evaluation.

Seattle Department of Transportation. (2011). Citywide Paid Parking Study Technical Report. January 14, 2011.

Shoup, Donald C. (2011). *The High Cost of Free Parking*. Chicago, IL; Washington, D.C.: Planners Press.

Suarez de Balcazar, Yolanda, Stephen B. Fawcett, and Fabricio E. Balcazar (1988). “Effects of environmental design and police enforcement on violations of a handicapped parking ordinance.” *Journal of Applied Behavior Analysis*, 21(3), 291-298.

Tversky, Amos, and Daniel Kahneman. (1974). “Judgment under uncertainty: Heuristics and biases.” *Science*, 185(4157), 1124-1131.

Tversky, Amos, and Daniel Kahneman. (1981). “The framing of decisions and the psychology of choice.” *Science*, 211(4481), 453-458.

Van Horn, John. (2007). “System data shows half of meter income goes uncollected.” *Parking Today*. 24-25. March 24, 2007.

Von Neumann, John, and Oskar Morgenstern. (1947). *Theory of Games and Economic Behavior*, 2nd rev. ed. Princeton, NJ, US: Princeton University Press.

Yang, Shuguan, and Zhen (Sean) Qian. (2017). “Turning meter transactions data into occupancy and payment behavioral information for on-street parking.” *Transportation Research Part C: Emerging Technologies*, 78, 165-182.

8. APPENDIX A

Field Data Collection for Testing Irrationality in Metered Parking

Goal for field data collection:

The goal for field data collection is to collect comprehensive and precise information about parking events and parking surveillance for the sampled block faces during the observation period. The field data will represent attributes of "real world" on-street parking in downtown Denver.

Key Points:

- Do not collect personally identifying information about travelers.
- We will attempt to capture each parking event (e.g., arrival, departure, payment) on the sampled block face during the observation period and its related attributed.
- Students who collect field data are trained and supervised by project faculty members (PIs) to be safe and aware while in the field.
- Students who collect field data will wear nametag holders with a student ID.

Survey interviewer selection and training:

[Name], a graduate student researcher, will lead the field data collection. If we hire additional CU Denver students to collect field data, we will select and train them according to this protocol and [Name] will supervise them in the field. The training for field data collectors includes:

- Data collection methodology (i.e., sampling strategy, correct recording while in the field, avoiding personally identifying information, etc.).
- Aims and scope of project.
- Safety (i.e., spatial awareness, not revealing personal information, setting boundaries).
- Confidentiality (i.e., not recording identifying information, not discussing field observations with anyone outside of research team, etc.).

Field data collectors ([Name] and any additional students) will debrief daily or weekly as a team, and will be encouraged to express difficulties and challenges as they arise. Data collectors will carry cell phones to make emergency calls as well as to make calls to the project PIs in order to clarify procedure, if needed.

Needed equipment for field data collection:

- Nametag and student ID
- Cell phone
- Map of area to be observed during the observation period
- Clipboard, data collection instrument, and writing instrument

Selecting block faces for inclusion in the study area:

In advance of going into the field, we will create a sampling strategy based on secondary data of parking events. The sampling strategy will account for the location and time of historic parking events in order to capture a representative sample of contemporary parking events.

Observing parking events:

For each block face:

- Record location and observation start time in the data collection instrument.
- Establish awareness of the parking poles on the block face and make a diagram.
- Take a census of vehicles parked at the observation start time, noting the meter pole number, meter status (e.g., time remaining, expired), and citation status (e.g., citation, no citation).
- To help keep track of arrivals and departures, write a generic description of the vehicle associated with the meter pole, e.g., white pickup truck, blue sedan, red SUV.
- For each parking departure, note the time of departure and any remaining time on the meter.
- For each arrival, note the meter pole number, generic vehicle description, time of arrival, time of payment, time on meter, time of departure.
- We will compute variables such as amount paid, length of parking event and overstay time separately.
- If a traveler pays for more time on the meter, make a note of the time at which money is added, and the time remaining on the meter.

Example of data collection instrument

Data collection for 14th and Larimer, north side, 14:00–16:30

Pole	Arr	Veh	Time on meter	Time of payment	Parking session	Citation	Depart time
14-1	-1	White pickup	00:14	-1	-1	0	14:31
14-2	-1	Blue sedan	1:36	-1	-1	0	15:28
14-3	-1	Red SUV	1:15	-1	-1	0	14:00
14-4	-1	Unoccupied	00:00	-1	-1	-1	-1
14-4	14:05	Blue SUV	2:00	14:07	1	0	-1
14-4	14:05	Blue SUV	2:00	16:00	2	0	-1

9. APPENDIX B

Field Data Collection Instrument

Study Date	Study Start Time	Study End Time	Name of Recorder	Street Name

	Pole Number	Vehicle Description	Arrival Time	Time of Payment	Time on Meter Post-Payment	Time of Second Payment	Time on Meter Post-Second Payment	Departure Time	Time on Meter Post-Departure	Time Inherited	Time of Surveillence 1	Time of Surveillence 2	Citation Issued During Observation	Notes	Reason for DNR (if applicable)
Baseline Data															
Observed Data															