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Parking, transit and traffic: Evidence from SFpark

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Abstract: Demand-responsive parking pricing programs, in which parking is priced based upon occupancy, are increasingly being used in cities experiencing rapid growth as a way to optimize parking. Despite the potential of demand-responsive parking in minimizing parking-related externalities, there are few empirical estimates regarding the effects of parking management policies, particularly around transit usage and traffics flow. We use data from SFpark, a demand-responsive on-street parking pricing program for the city of San Francisco, along with a rich micro data-set on transit bus usage from the San Francisco Municipal Transportation Agency. Using a difference-in-difference strategy, we find that SFpark is associated with sizeable increases in transit bus usage of about 21 and reductions in lane occupancy of 5 percentage points per census block. Our welfare computations suggest economic benefits of $36 million over the duration of the program (2011-2013) resulting from avoided pollution due to increased transit usage and from reduced congestion. These benefits easily exceed the nominal costs of the program. Our results not only suggest that demand-responsive pricing programs achieve their stated goals, but also mitigate many traffic-related externalities, yielding significant welfare benefits

Keywords: Parking policy, transportation, mass transit, air pollution

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1. Introduction

Parking is a growing problem in U.S. cities due to the increasing growth in population and automobiles, reflecting the fundamental fact that cars remain parked about 95% of the time (Marsden 2006; Shoup 2011). Excess demand for parking is widely acknowledged to be a contributing factor to increased congestion in urban areas. Cities experiencing rapid increases in automobile usage have focused largely on policies aimed at reducing entry into the most congested areas using policies such as road tolls or congestion pricing, where motorists entering the central business district pay a fee during peak hours (Albert and Mahalel 2006; Hess 2001; Albert and Mahalel 2006; Hamre and Buehler 2014; Fosgerau and de Palma 2013; Verhoef et al. 1994; Gibson and Carnovale 2015). When optimally set, such charges rationalize traffic entering the city center.

Nonetheless, there remains the problem of optimizing on-street parking, since this can contribute to congestion within the central region (van Ommeren et al. 2012, van Ommeren et al. 2011). More importantly, parking charges in many cities are sub-optimal along many dimensions: their levels are often too low and they are unresponsive to rapidly changing demand. At best, they reflect a time-of-use policy, varying between the day and evenings, with the levels of charges revised infrequently and only loosely based upon demand, with administrative and time-enforced limits complementing these demand invariant charges. In view of the academic literature suggesting that it is more beneficial to allow prices to vary with demand at some temporal aggregation (Shoup 2006), cities have recently begun pursuing demand-responsive pricing programs. The primary goal of these programs is to use parking spaces more efficiently by encouraging turnover and increasing parking availability, and the mode chosen is differentially pricing parking based on occupancy. As a result, not only do more popular parking spots or times have higher meter rates compared to areas with lower occupancy but these rates vary with occupancy at some time aggregation, potentially generating more turnover than flat meter rates or time enforced limits.

Equally important, policies targeted toward parking, similar to those related to congestion charges, could also lead to altered trade-offs between public transit and private automobile ("auto") usage, since parking prices and availability have repeatedly been cited as strong motivators for driving in travel surveys (SFMTA 2016). Consequently, there are additional channels for welfare enhancement, beyond those directly envisaged by the policy. While estimating the effects of changes in aggregate travel patterns and mode by measuring the reduction in vehicular usage is an active area of research for congestion charges (e.g., Gibson and Carnovale 2015), little is known regarding how changes in parking management affect travel mode at the city-block level, the level at which parking management rules vary.

In this study, we investigate the effects of the SFpark program ("SFpark"), a demand-responsive pricing parking program in San Francisco administered by the SFMTA. The explicit goal of SFpark was to link parking price to on-street parking occupancy, with the aim of reducing cruising for parking. We use the fact that the SFMTA made no explicit changes to bus schedules consequent to SFpark. In addition, while parking price changes were exogenous to individual travellers, they were endogenous at the aggregate scale: price changes, in direction and magnitude, occurred every rate adjustment period (of about 8 weeks) depending upon the previous period's occupancy. Thus, the magnitude and direction of price change at each block could not have been known a priori by any individual traveler, ruling out any rational way of anticipating the effects of the program, unlike for other policies such as road tolls.[1]

[1] This aspect is similar in setting to studies of dynamic pricing of electricity: the consequence of many individual consumption decisions determine the aggregate electric price (spot price). Consequently, the price is exogenous to each individual (while endogenous at the system level), indicating that no individual is rationally able to change his behavior in anticipation of effects.

We focus on two aspects of the relationship between parking and urban transportation that have been discussed in largely disparate literatures, transit usage and traffic flow. SFpark could potentially affect the travel mode split at the aggregate parking block level by encouraging either auto use, if the effect of better availability of parking slots due to increased parking turnover is dominant, or an increase transit ridership if the effect of increased parking price is dominant. Consequently, while one may anticipate a reduction, the magnitude of the overall effect on traffic flow is not evident in the absence of any prior empirical evidence. We are also interested in the effects on traffic flow in view of the explicit goal of SFpark to reduce congestion. While prior studies (Millard-Ball et al. 2014, Chatman & Manville 2014) have shown that SFpark is associated with decreases in cruising for parking, there has been no similarly rigorous evaluation regarding the effects upon overall traffic flow.

We use data from the SFpark pilot evaluation for on-street parking, which includes hourly data on parking occupancy, metered rates and measures of daily traffic flow, between July 2011 and July 2013. We supplement these data with a rich, detailed panel data set on the SFMTA's Muni transit bus system in San Francisco that includes information on bus ridership at a given time and bus stop for all bus lines. We use these data, along with urban U.S. estimates for pollution and San Francisco-specific figures for congestion costs, to quantify the effects on transit usage of the implementation of SFpark and assess the environmental and economic effects of the program.

Our findings shed light on several aspects of urban transport that relate to parking. First, we find a positive effect of SFpark on transit usage, indicating an increase in passenger traffic of about 21 per time-band and block, which is robust to different specifications, indicating that mode choice is responsive to parking-price. This is a result that is commonly reported in stated-preference studies, but has not, to our knowledge, been quantified at the scale of census blocks using very detailed public transit ridership data.[2] We also find SFpark is associated with reduced traffic flow, with daily average lane occupancy falling by a sizeable 5 percentage points (representing a 29% reduction in average daily occupancy), while another measure of flow, vehicular count, falls by 4 vehicles, although this result is insignificant. We also observe some variation across the two-year period of SFpark, with a reduced yet significant effect towards the end. Using estimates of avoided pollution and travel patterns for San Francisco city, we find welfare gains of $36 million over the two-year duration of the pilot program, a sizeable figure for a policy that envisaged rather moderate changes in parking charges.

Our study is, to our knowledge, the first to provide a well-identified estimate of the changes in transit usage attributable to parking pricing and management. Further, our estimate of the effects of parking management and pricing upon traffic flow are among the few in the literature. They also provide a complementary perspective to a previous study for SFpark focused on cruising by Millard-Ball et al. (2014). Our study contributes to the very sparse empirical literature regarding the effects of pricing parking (van Ommeren et al. 2011, Millard-Ball et al. 2014; Pierce & Shoup 2013a; SFMTA 2014; Chatman & Manville 2014) and complements the related theoretical literature examining the effects of parking upon congestion (Arnott & Rowse 2009; Arnott & Rowse 2013). Our work also relates more broadly to renewed interest in many fields of applied economics in minimizing external costs and increasing efficiency of use by aligning pricing of a good more closely with the true cost of its provision. This is an issue of particular significance to markets where supply is capacity constrained, investments in capacity expansion are expensive, and demand is time-varying. These characteristics are shared by markets as diverse as urban

[2] We note that the evaluation of many congestion charging pilot projects used travel surveys post-change to obtain a picture of the change in travel mode post-change. For instance, in an evaluation of the effects for the congestion charging pilot for Stockholm, Eliasson et al, 2006 used travel surveys to elicit aspects related to modal shift. See also §3.7, Eliassson, 2014 for a discussion.

transportation (road capacity is the constraint) and electricity (generation and transmission capacity are relevant constraints). To illustrate, dynamic pricing in electricity, where a consumer is charged the real-time price for providing electricity, has been the focus of significant academic and policy effort (Borenstein 2005; Holland and Mansur 2006; Joskow and Wolfram 2012). In fact, even congestion charges have been time-varying in certain cities (e.g. Stockholm and Singapore), reflecting the time-varying nature of demand for road travel.

The rest of the paper unfolds as follows: §2 contextualizes our questions by relating them to the relevant literature. §3 provides an overview of the different data sources, while §4 investigates the effects of SFpark on bus transit usage. §5 considers the effects upon traffic flow and §6 provides an approximate estimate of the welfare gains resulting from SFpark. §7 provides a discussion of results and concludes with some policy implications. Additional details regarding the data preparation and the layout of SFpark, along with results for additional specifications or robustness checks, are presented in the Appendices.

2. Background and related literature

Many global cities experiencing rapid urban growth have considered using demand-responsive pricing programs to address the growing disparities between parking demand and supply (Wang and Yuan 2013; Asian Development Bank 2011; Mingardo et al. 2015; Kondranksy and Hermann 2011). In fact, a few studies in Europe show that appropriately pricing parking is an important feature of an effective parking management strategy (van Ommeren et al. 2011; Fadeyev 2017; Barter 2009). However, due to scarce parking data, few studies have rigorously examined the effectiveness of these programs. As a result, the combination of SFpark data and the rich Muni bus data that we use offers a unique opportunity to evaluate these programs along several important dimensions.

Prior to SFpark, San Francisco, like many other U.S. cities, used traditional parking policies which included time limits or flat meter rates that were updated periodically by the San Francisco Board of Supervisors based on recommendations by SFMTA. Meter rates did not vary over time, but varied by location, where prices were highest in downtown ($3.50 prior to SFpark) and lower in neighborhood commercial districts ($2.00). However, it is unclear if flat meter rates or time limits are an effective strategy to increase parking turnover since enforcing these limits is challenging.

SFpark was approved in 2008 and commenced in July 2011 (SFMTA, 2014). We use data specifically from the SFpark pilot program, which was carried out between July 2011 and June 2013. The program included seven parking management districts in the treatment blocks (the Civic Center, Downtown, Fillmore, Fisherman's Wharf, Marina, Mission, and South Embarcadero) and two in the control group (Inner Richmond and Union) at which parking rates did not change. Together they encompass 6,000 metered parking spaces or 25% of the city's total on-street parking. The main goal of SFpark was to improve parking turnover and availability through demand-responsive pricing, which could vary over time and across blocks. On-street metered parking rates change based upon average occupancy over the previous rate adjustment period. Each rate adjustment period lasts 8 weeks. The target occupancy range is 60-80% per block-face and time band. Time bands are separated into morning hours (7am to 12pm), early afternoon (12pm to 3pm), evening hours (3pm to 6pm) and night hours (after 6pm).[3] If average occupancy in the previous period fell within the target occupancy range, prices did not change. However, if average occupancy exceeded 80% in the previous period, then hourly parking rates increase by $0.25 per

[3] Block faces in Downtown, Fillmore, Fisherman's Wharf and South Embarcadero had metered parking after 6pm prior to SFpark. In the Fillmore parking management district, meter rates after 6pm started during rate adjustment period 9 (February 2013).

hour. If occupancy rates fell between 30 and 60% or < 30% then parking rates decreased by $0.25 and $0.50 (resp.). Updates to parking rates are posted by the SFMTA on SFpark's website at least 7 days prior to the change. Hourly rates could not exceed $8.00 per hour or go below $0.25 per hour. SFpark also allowed for longer time limits of up to 4 hours instead of 1 or 2 hours. Overall, non-price-related changes made parking more convenient.

The SFMTA conducted its own evaluation of SFpark's pilot program and found that parking met the target occupancy range at a higher rate at pilot blocks compared to control blocks (SFMTA 2014). It also reported congestion relief, specifically traffic volume and speed, along very congested routes. While these results are informative, the study was largely restricted to a simple comparison of outcomes. It did not account for control variables or other differences between treatment and control, making it difficult to assess questions related to causality. There was also no assessment of the effects upon other forms of transportation, such as public transit. Consequently, we build upon the existing work to further examine impacts on urban transportation.

While economists have been increasingly using empirical approaches to explore important large-scale questions related to urban transportation, such as the value of urban transit (Anderson, 2014), the potential of urban transit to provide congestion relief in U.S. cities (Duranton & Turner, 2011) and the effect of congestion pricing upon air pollution (Gibson and Carnovale, 2015), the empirical literature on the relationship between parking policies and urban transportation remains small, possibly due to scarcity of appropriately detailed data sets.[4] There is a theoretical literature aimed at assessing the effects of parking upon economic outcomes as well as congestion (Arnott & Rowse, 2009; Arnott & Rowse 2013; Inci, 2015), of which only a few studies relate parking

[4] Using the rich parking-related data set from SFpark's pilot evaluation program, a few academic studies have already examined certain aspects of SFpark. A study by Millard-Ball et al. (2014) found that SFpark moved occupancy rates closer to the target range and reduced cruising. Other studies by Pierce & Shoup, (2013a) and Millard-Ball et al. (2013) examined parking price elasticities based on SFpark.

directly to travel mode choice (e.g. Voith 1998). Empirical studies on parking still make up a small portion of the parking-related transportation literature and many gaps remain. Even less is known regarding the impact of parking policies on modal transportation choice, which only a handful of empirical studies have addressed explicitly (e.g., Gillen, 1977; Heshner & King, 2001; Merriman, 1998; Millard-Ball, Weinberger & Hampshire, 2014). While early analyses of SFpark suggest SFpark has been successful thus far in achieving some of their target outcomes, particularly parking availability (e.g., Millard-Ball, et al. 2014; Pierce & Shoup, 2013a; SFMTA, 2014, Chatman & Millard, 2014), more empirical research is needed to discern other outcomes of interest for policymakers, including impacts on public transit and the effects of new meter installations.

3. Data and empirical approach

We use data from SFpark's pilot evaluation, which includes information on meter rates for each block face, time band and rate adjustment period. We have data from April 2011 to July 2013 on both pilot and control block faces within a given parking management district (Figure 1). The first rate adjustment period for block faces varies between July 21, 2011 (89.9% of observations) and October 4, 2011 (1.3% of observations). Since we are also interested in parking policies, we include information on block faces where new meters were installed as part of SFpark, which accounted for 1.8% of SFpark block faces (Figure 1). Newly installed meters are likely of interest to policymakers since anecdotally businesses are concerned with its effects on foot traffic and sales, though there is little empirical evidence of this (Hymel 2014)). Prior to their installation, these block faces had either no parking limits or time-enforced limits, which can be difficult to enforce. More information about these data are in Appendix A.1.

We also use daily traffic data, specifically lane occupancy and vehicle count, collected as part of the SFpark pilot evaluation. Lane occupancy is defined as the average percentage of time over a twenty four hour period) a detector is occupied by a vehicle. Similarly, vehicle count is the average number of vehicles passing over a detector in a twenty-four hour period. Roadway sensors were installed at 56 locations throughout the city in participating parking management districts, which included 46 access points, 62 repeaters, and 346 sensors (SFMTA, 2013). In consequence, our traffic outcomes pertain to far fewer blocks than actually participated in SFpark.

Finally, we obtain a rich data set of 14.8 million observations at the bus stop level for the Muni bus system, which is the main transit bus system in San Francisco, through a public records request with SFMTA (Figure A1). These data include detailed information on the number of people who embark and disembark at each bus stop for every bus line and time point on weekdays. These data are only available during certain seasons of the year, so for this study, we focus on October to December for years 2009 to 2013. Weekend data are only available in 2010 so we focus our analysis on weekdays. Using these data, we provide the first empirical estimates of the effects of demand-responsive parking upon transit usage and quantify the modal shift at the micro level. Further discussion related to merging the Muni transit bus data with SFpark data and 2010 U.S. Census data is provided in Appendix A.2.

Table 1 shows summary statistics, where panel A shows the number of people embarking and disembarking at bus stops within 500 ft of a census block for a given time band and date for all blocks with a bus stop and panel B shows daily traffic measures for SFpark for SFpark pilot evaluation blocks only that had roadway sensors within 500 ft. From Table 1, it is evident that more people embark and disembark at bus stops in the SFpark pilot evaluation blocks relative to other control blocks. We also show that transit usage is greatest for time bands 1 and 3, which represent morning and evening hours. Panel B indicates higher lane occupancy and vehicle counts on SFpark pilot blocks relative to control blocks, as well as on weekdays relative to weekends.

4. Transit bus usage

An understudied topic in the transportation literature is how parking influences mode choice at both the individual and the aggregate level. For the case of San Francisco, parking appears to play an important role in determining travel mode choice, based at least on repeated stated preference surveys. A 2015 travel mode share survey by SFMTA (2016) of Bay Area residents, including San Francisco, found that 23% of residents relied on public transit, while 47% used a private automobile. When asked what motivated them to drive, the greatest influences were speed and convenience, then distance between the destination and parking and parking price, where 50% of residents considered parking prices as being “free or cheap" as a strong motivator to drive. Of the respondents that reduced the number of cars in their household, 9% cited lack of parking as a major reason, while 4% considered expensive parking costs as a factor. Another survey in 2005 of the San Francisco Bay Area found that if parking were free, only 5% of commuters would take the bus and 75% would drive alone (SFMTA, 2014). However, if parking was not free, then 43% would take the bus and 37% would drive alone. These survey results suggest SFpark could influence commuters’ mode choice via metered parking rates, though no study has examined this empirically using micro-level public transit ridership data. Building on surveys such as these, our analysis considers the effect of parking policies on aggregate transit usage. In view of the modal split for SF city, with automobiles and buses predominating, this then implies an aggregate change in pattern of auto usage, implying a modal shift.

4.1. Regression framework

We investigate the effects that SFpark exerted across rate adjustment periods on transit bus usage using very detailed Muni bus ridership data, specifically at the census block-time band level. Examining variation in transit usage at a high spatial resolution is helpful when studying urban transportation since neighborhoods can vary dramatically at the block-level. Additionally, by looking at impacts within days, we can evaluate whether SFpark affects transit usage at times of high congestion, such as the morning and evening rush hour, when public transit is most valuable (Anderson, 2014). Our analysis focuses on weekdays for the time period of October, November and December for the years between 2009 and 2012.

Since the intention of SFpark is to improve parking availability, it did not involve any reconfiguration of bus routes and schedules. As a result, we anticipate that any differences in ridership usage identified between SFpark and non-SFpark blocks are largely driven by SFpark itself. In view of the exogeneity of SFpark, we use a difference-in-difference (DiD) framework, where control blocks are any blocks for which we have Muni bus data that are not part of the SFpark pilot program in San Francisco (Figure A2). We assume there is no increase in general traffic and economic activity in the pilot regions relative to the control after accounting for relevant covariates, including fixed effects along many dimensions and neighborhood-specific time trends.

Next, we evaluate the key assumption for DiD analysis, that of the “common trend”. Consider a plot of the average daily pre-SFpark (i.e., before 2011) ridership trends for weekdays in Figure 2. While control blocks (dashed line) have an overall lower level of ridership compared to pilot blocks (solid line), it is evident that trends for pilot and control blocks are similar in the pre-SFpark period. This suggests that the common trend assumption is at least very plausible. We revisit this question again in §4.3, where we use other methods to strengthen its plausibility.

The time period relevant to the treatment is an eight-week rate adjustment period, denoted z, commencing, as already indicated, on July 12, 2011. Thus, our sample consists of data for rate adjustment periods 2, 3, 7 and 8, and three "rate adjustment periods" prior to the commencement of SFpark.[5] Our baseline regression thus is:

$$ridership_{znct} = \gamma_0 + \gamma_1 SFparkPilot_{zct} + rate\_adjustment\_period_z + \gamma_3 neighborhood * year_{nt} + \boldsymbol{time_t} + census\_block_c + \rho \boldsymbol{W}_t + \omega_{nct} \qquad (1)$$

where the dependent variable, *ridership*, is the total number of people who embark and disembark at bus stops within 500 ft of the centroid of census block c in neighborhood n in rate adjustment period z and time block, date level t. In view of our interest in understanding the flow of travelers across SFpark blocks, this is the most natural candidate since it accounts for both inflow and outflow to a block. The independent variable of interest is on the interaction term, where *SFparkPilot* is a dummy variable equal to 1 if the rate adjustment period is ≥ 1 and the block b is designated a pilot block by SFpark, otherwise it equals 0. We also include a rate adjustment period FE (*rate_adjustment_period*), which represents a FE for every 8-week rate adjustment period, starting July 12, 2011, which is the beginning of the first rate adjustment period.[6] Note that like all time fixed effects that are not interactive, the rate adjustment FE does not vary over pilot and

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[5] Due to data constraints, the *rate_adjustment_period* variable varies during the pre-SFpark period. The first pre-SFpark period represents the period between October 1 and November 30, 2009, the second pre-SFpark period is between October 1 and November 25, 2010 and the final pre-SFpark period is between November 26 and December 31, 2010. Since these divisions are arbitrary, it should not affect results.

[6] Not all block faces had "smart parking" activated on the same day, July 12 2011. To account for this, we consider the start of any treatment period as the earliest start date any block was included in SFpark and the latest end date for any block as the end of the treatment period. This approach, while more accurate, may lead to reduced precision due to variation in sample size. Nonetheless, since only a very small proportion of blocks (about 11%) did not commence smart parking on July 12 2011, the reduction in precision is not of much concern. In any case, this aspect is explored in §4.3

control blocks, and when translated into a standard panel DiD setting, the rate adjustment period is our key measure of time, and a census block is the unit where treatment occurs. Thus, the rate adjustment period FE corresponds to the more common time-fixed-effect in panel DiD settings while the census block FE (*census_block*) corresponds to the "individual fixed effect". We also control for daily weather in ***W***, specifically maximum temperature and precipitation, since its likely influences the choice driving and using the bus. Additionally, we account for annual trends at the neighborhood level that could affect bus ridership and general economic activity (*neighborhood*year*). In view of the sizeable differences between neighborhoods in key aspects, including economic activity, this effect captures the time varying differences across different neighborhoods. Finally, in ***time***, a vector of time-related fixed effects, we include a week FE to control for holidays and seasonality and a time-band FE to account for differences in transit ridership within days.

Our coefficient of interest, γ_1, represents differences in ridership between pilot and control blocks after SFpark was implemented.[7] However, it is unclear if γ_1 should be positive or negative. If parking supply constraints were the main reason individuals used the bus instead of driving, then we expect $\gamma_1 < 0$ due to improved parking availability or convenience through SFpark. However, we could also expect $\gamma_1 > 0$ if meter rates in high-demand areas increased and exceeded some drivers' willingness to pay, prompting them to substitute the car with the bus. In addition to demand-responsive parking, SFpark also made on-street parking more convenient by allowing for the use of credit cards at meters and other mechanisms, including wide dissemination of information regarding parking. Consequently, we do not observe the effect of constituent policies of SFpark, only of SFpark as a whole, As already indicated, no changes in public transit

[7] More specifically, the coefficient γ_1 is identified by the deviation in transit usage from census block-rate adjustment period-time block means (between the SFpark pilot and control blocks).

characteristics (routes, frequency across pilot and control blocks, and bus characteristics) occurred consequent to SFpark. As a result, attribution of changes in transit usage to SFpark itself is possible.

4.2. Results

Results are in Table 2, where each column represents a different regression. The average number of people embarking and disembarking at bus stops within 500 ft of the census block at SFpark pilot blocks on weekdays between 2009 and 2012, for the period October to December, is 185. The same average for all other control blocks, including SFpark control blocks and any block that has a bus stop and was not part of the SFpark pilot evaluation, is 71. Other summary statistics for transit usage are in panel A of Table 1. Column 1 shows results using equation (1) and we find a positive, significant relationship between SFpark and transit usage, implying that ridership increases by 21 people (p<0.01) following SFpark on pilot blocks relative to the control blocks and prior to SFpark. This represents an increase in ridership of 11% for an average SFpark pilot block for a given day and time band.[8]

Next, we consider how results vary across census blocks. As part of SFpark, some pilot blocks included new parking meters at blocks where parking was previously unregulated or had time limits. In view of the results of an SFMTA travel survey, where residents identified free parking as an important factor in driving, transit ridership could possibly increase at blocks with

[8] We also find our baseline results here, and in §5 regarding traffic volume, are robust to using different temperatures splines or including a quadratic term in neighborhood-year trends. We also consider impacts on those who embark (i.e., boardings) only using equation (1) to address possible concerns that the total number of people who embark and disembark may not properly reflect transit usage. We find a positive significant effect of SFpark on those who embark of 6.5 people (p<0.05), which represents 17% of the average number of people who embark. This is in line with our main results in Table 2. In the interests of simplicity, we only provide results pertaining to the simpler specification in eq (1) above. Results for the spline specification, as well as those pertaining to (the number of individuals) boarding as the dependent variable, are available upon request.

new meters where parking is no longer free. We interact our independent variable of interest with a dummy variable equal to 1 if any part of the block is newly metered. Results for this specification (column 2) indicate a positive, but insignificant, effect of SFpark.

Our results indicate that demand-responsive pricing programs for on-street parking help stimulate transit usage in urban areas, which could ameliorate congestion and improve air quality. The externality reduction from these two factors are quantified in §6. Importantly, our results suggest changes from other travel modes, predominantly automobile, to transit as being the source of increases in transit usage. We discuss this aspect in greater detail in §4.5.

4.3. Alternative specifications

We evaluate a few alternative specifications focused on two aspects that have received attention in the transportation and other policy-evaluation literature: variation of the effect of SFpark over different rate adjustment periods; and within day travel substitution. We defer questions regarding the interpretation of some of these results to §4.5.

Turning to the first aspect of interest, we aggregate rate adjustment periods into different "treatment periods" and evaluate whether the effect of transit varies across these periods. We begin with two treatment periods first, where a newly defined variable, "treatment period 1", includes rate adjustment periods 2 and 3, and treatment period 2 includes rate adjustment periods 7 and 8. We may expect differential impacts between treatment periods 1 and 2 as travelers learn about the effects of SFpark and re-optimize. Results from these regressions are in columns 3 and 4. We find that in treatment period 1, transit ridership increases by 30 passengers (p<0.01), and a smaller, yet significant effect in treatment period 2 of 10 people (p<0.01). When a third treatment period is included (treatment periods 1 and 2 are represented by rate adjustment periods 2 and 3 respectively while treatment period 3 is represented by rate adjustment periods 7 and 8), we observe the same pattern in column 5. We find a reduction in transit bus usage from a high of 34 to a low of 10 riders, where all coefficients are significant. It appears that there is a substantial amount of learning and re-optimization involved, where the initial effects of SFpark are three times larger than impacts in later rate adjustment periods in this study period.

Next we assess the effects of SFpark on different time bands, since one hypothesis is that SFpark is likely more effective during periods of high congestion, such as the morning and evening rush hours. We interact *SFparkPilot* with different time bands, where the reference category is after 6pm, and results are in column 6. We find a statistically significant increase in transit usage during the morning and evening rush hours of 71 and 28 (resp.) ($p<0.01$). We also find a *negative* significant effect on ridership during the afternoon of 23 passengers ($p<0.01$).[9] In view of our empirical set-up having already accounted for fixed or time-varying aspects of demand for public transit, these patterns are very suggestive of substitution of auto usage over time, including individuals re-optimizing over trip time, aspects we discuss in §4.5.

4.4. Robustness checks

We begin by testing for possible selection bias and reduced precision resulting from different start dates. Approximately 90% of block faces that were part of SFpark started on July 21, 2011, and the remaining 10% of pilot block faces started at later dates. In the main specification, we do not allow for systematic differences in blocks that started on July 21, 2011 relative to those that started later, differences which could be correlated to factors that affect bus

[9] We also consider the impacts of blocks with newly installed meters, both for different treatment periods (in column 6) and different time bands (in column 9) and find no significant effects. There were also no effects (Column 4) of restricting the sample only to blocks which started SFpark program on July 11, 2011 (see §4.4 for discussion).

ridership. We test for this by only examining pilot blocks where at least one block-face started SFpark on July 21, 2011 and drop blocks that started afterwards. This reduces our sample size by 0.3%. Results are in column 8 and we find the coefficient on *SFparkPilot* is positive, significant ($p<0.01$), and almost identical in size to the main findings in column 1. This suggests that blocks that started at a later date are not systematically different from those that started on July 21, 2011.

Next, we examine whether the increase in transit ridership is affected by restricting our control sample to blocks explicitly designated as SFpark control in the pilot evaluation. This allows us to assuage concerns that our effects are driven at least in part by the fact that non-SF park control blocks are systematically different from those included in SFpark in ways which enhances our treatment effect. Note that our use of the entire sample of census blocks in SF city is intended to both increase precision and to account for the under-sampling of SFpark control blocks which are far fewer in number than the pilot (see Table 1).[10] The average number of people embarking and disembarking at bus stops within 500 ft of the census block at SFpark pilot blocks on weekdays between 2009 and 2012, for the period October to December at SFpark control blocks is 111. We also assess if the common trend assumption holds for these blocks and find similar trends in transit bus ridership before SFpark (Figure A6). We use equation (1), but since the sample size and number of blocks we observe is dramatically smaller compared to the main results, we focus on our baseline model as well as specifications focused on blocks with new meters. Results are in Table A1, and we find positive significant impact of 10 people ($p<0.05$) in column 1 using the baseline equation. We also find a similar result if we consider the effects at blocks with new

[10] Recall again that the differences between SFpark control blocks and other census blocks in San Francisco city (included in SFMTA data used) along both time-invariant (captured by census block fixed effects) and key time-varying dimensions (captured by the neighbourhood-specific time trends and time fixed effects) are already accounted for in our specification. Thus, the fact that SFpark pilot blocks, SFpark control blocks, and non-SFpark census blocks differ in e.g. average ridership is already accounted for, and is unlikely driving our results in the baseline, in table 1.

meters in column 2. Next, in columns 3 and 4, we consider blocks that started on the July 21, 2011, and find positive, marginally significant results. While our sample of census blocks dramatically shrinks when restricting analysis to only SFpark control blocks, our findings are qualitatively unchanged.

Further, aside from using Figure 2 to demonstrate similar trends for pilot and control blocks, we also test for this by using equation (1), but only include observations prior to SFpark. Instead of the variable *SFpark*, our independent variable of interest is an interaction between a dummy variable for pilot blocks and a rate adjustment period trend, which represents changes in transit ridership across approximate 8-week (pseudo-) rate adjustment periods prior to the commencement of SFpark. We also include a rate adjustment period trend, and the remaining control variables in equation (1). To the extent that the "common trend" assumption is valid, one anticipates the coefficient on the interaction between the pilot dummy and rate adjustment period trend to be not significantly positive. An insignificant result indicates no bias at all while a negative coefficient indicates in fact that the treatment effect is, if anything, under-estimated (i.e. biased downward). Results are in column 1 of Table A2 in the Appendix and we find a *negative*, significant effect on ridership at pilot blocks across rate adjustment periods, suggesting reduced transit ridership at these blocks prior to SFpark. We perform the same exercise using control blocks used in the SFpark pilot evaluation only and find similar results in column 2. This implies that our main results in Table 2 may, if anything, underestimate the true effect of SFpark on transit usage.

4.5. Discussion

In this section, we first evaluate a few alternative mechanisms behind the increase transit ridership we find as well as explain why the magnitude of our results are reasonable. Next, we examine if the timing of our results are consistent with other interpretations in the literature, including responses to widely publicized public programs and the persistence of policy interventions. Finally, we discuss how our study differs from other work focused on evaluating the effects of congestion charges.

Individuals faced with an altered parking management regime can respond by: postponing their trip, rescheduling it, changing mode to bus, to not respond at all, or to park elsewhere. Our findings indicate that in the absence of rescheduling trips, travelers *on aggregate* appear to respond by changing mode between transit and non-transit travel, which we argue is auto usage. While being unable to explicitly demonstrate this, lacking data on auto usage, we nonetheless indicate why alternative explanations of our main results are much less plausible. Other explanations for our results include an increase in trip generation among all transportation modes or individuals switching from other non-auto travel modes (e.g., subway, biking, walking) to transit buses.[11] We do not consider these plausible arguments for a few reasons. First, in equation (1) we control for flexible fixed effects across different temporal and spatial dimensions and flexible neighborhood-year trends. These controls accommodate most common aspects affecting differences in trip generation or these other non-auto modes between treatment and control blocks, along with weather-related controls that are common determinants of public transit and non-automobile travel modes. Also, it is not obvious why individuals would shift from walking and biking to buses in sizeable enough numbers during the SFpark pilot period since these modes were not directly affected by SFpark. Additionally, other studies suggest

[11] We ignore postponement of trips since they cannot explain the finding of an *increase* in transit usage.

different forms of public transit are designed to complement, not necessarily substitute, each other (e.g., Anderson, 2015). Also, as already detailed, no changes to public transit schedules, including the BART system, were made. Together with the rather marginal price differences induced by parking rate changes, these other mechanisms seem far less credible.

Next, we discuss how our results differ from studies focused on evaluating the impacts of congestion charges, which differ from the parking fee changes we consider here in many aspects: spatially varying changes versus a single, point fee; endogenous (demand-based) versus exogenous prices. Even in the case of congestion, there are many margins of choice available to the consumers, leading to difficulty in identifying precisely which changes led to the observed change (Eliasson, 2014). Without a fully-specified structural model or a detailed travel survey, it is not possible to precisely estimate the magnitude of each of these changes and how they relate to one another. The difficulty in estimating the effects of different dimensions of choice involved acquires greater force in our case, since changes in parking fees involves an additional margin of choice (e.g. parking elsewhere). Consequently, we are most interested in examining one of these dimensions of change: the overall effect of the SFpark program, viewing it, similar to the congestion examples, as a single set of changes. It is important to emphasize that we are able to estimate this effect precisely because SFpark did not involve any changes to public transit, unlike when road tolls are implemented (see e.g., Eliasson, 2014).

In view of these differences, we restrict ourselves to qualitative comparisons. One of our findings shows substitution over the day which has some similarities with substitution of trips to the unpriced "shoulder" periods for congestion charges. We find a reduction in transit usage during the afternoons, but increases during the morning and evening hours. This suggests substitution of travel modes, wherein travelers, including commuters, during the morning and evening peaks are preferentially shifting away from automobiles to transit. However, during the afternoon, often considered a more discretionary period, travel is overall substituting away from transit. It is likely that two aspects, net parking cost and price responsiveness, which together determine total trip cost and hence mode choice, are so aligned that the net effect, on aggregate, is a mode switch to automobile.[12] Our results showing a shift away from automobile during the morning and evening hours are consistent with prior travel surveys where commuters indicated sensitivity to parking costs. They are also consistent with the results in the congestion charge literature, which report a similar behavior during times overlapping with the morning and evening commute period (e.g. Gibson and Carnovale 2015).

We also consider if the magnitude of changes in transit bus ridership in our main results are reasonable based on the shift from auto usage to transit buses. We expect that only a small proportion of the population is responsive enough to SFpark that it alters their behaviour. This change then affects others who may be less price sensitive in ways that reduce the externality imposed by the inappropriately priced parking scheme. To get a sense of the figures involved, assume two persons to an average automobile; then, using the results in row 1 and column 1 of Tables 2 and A1, the implied average number of vehicles reduced on an SFpark pilot block is between 5 and 10 (resp.), which is between 3 and 5% of the average vehicles in an SFpark pilot block. Thus, while the magnitude of our findings are sizeable, they are consistent with only a sub-population being more responsive to the SFpark program. This is a comforting finding in view of the substantial uncertainty in the price elasticity for parking derived from the SFpark data (Millard-Ball et al. 2013, Pierce and Shoup, 2013a, Pierce and Shoup 2013b).

[12] Note that changes in travel model is determined by the interplay of two aspects: responsiveness of trips to parking costs (with discretionary travel often thought of as more responsive) and changes in net parking costs. The latter is defined as nominal parking cost plus the time-costs related to parking over time. If travelers are responsive to prices, the reduced net parking cost is likely to cause the mode choice to switch to auto usage.

Finally, our results are likely consistent with many interpretations and may encompass many changes in behavior. First, SFpark involved not only regular parking price changes over time and space but also information campaigns, additional measures such as making parking payments easier and clearer, and additional metering. Previous work suggests that constant exposure to new information from widely publicized programs may lead to an over-reaction, which could explain the increase in transit usage (e.g., Reiss and White, 2008). Other literature has shown that increasing the frequency in price changes, such as with SFpark, makes prices more salient than before (e.g., Gilbert and Zivin, 2014). Alternatively, questions related to persistence of policy interventions, including responses to different price and non-price interventions, are an active topic of research, and qualitatively our findings show that treatment effects decline over time, which is consistent with prior evidence (e.g. Allcott and Rogers, 2014). Overall, our results suggest that aspects such as habit persistence and switching costs, indicating difficulties in responding to price changes in the short-run, may not be of much concern for the moderate changes considered here.

5. Traffic flow

Next, we consider the effects of SFpark on two key measures of traffic flow using a variant of equation (1), and two commonly used outcomes: the average daily percentage of time a car was detected above the sensors (lane occupancy) and average daily vehicle count.[13] The relationship between parking availability and congestion has many facets, though most previous work focuses on possibly the most important one, cruising (e.g., Millard-Ball et al., 2014). Cruising for on-street

[13] Another measure of congestion we considered was average vehicle speed, however summary statistics showed that the average vehicle speed before and after SFpark were very similar, so we did not examine this outcome further. This is not unexpected since, as already referred to, SFpark blocks were mostly located by arterial roads where vehicle speeds are typically lower, with limited variability. Compare the location of highways and freeways in SF in Figure A5 with the SFPark pilot and control blocks from Figure A4.

parking is considered to be responsible for between 30 and 50% of traffic in downtown areas, suggesting it also influences traffic volume for cars passing through a street (e.g., Shoup 2006).

In this section, we focus on the effects of SFpark upon traffic volume using roadway sensors placed in the pilot and control blocks included as part of the pilot evaluation. Figure A3 shows the location of the roadway sensors and the pilot and control parking management districts where the on-street parking meters are located. We aggregate the traffic volume measures to the census block level by averaging the traffic volume measured across all roadway sensors located within 500 ft of the centroid of the census block. There has been, to our knowledge, no rigorous empirical evaluation of the effect of SFpark on congestion or traffic volume beyond the study of cruising by Millard-Ball et al. (2014). Our approach is the same as for transit usage: we use the exogeneity of SFpark block assignment and attribute the difference in a traffic flow outcome between pilot and control blocks, before and after "treatment", to SFpark.

In our baseline model for traffic, we include the same control variables as in equation (1), but substitute parking management district-year trends for neighborhood year trends, since a parking management district is the more appropriate aggregation at which factors that influence parking vary. Since we only have traffic data at the daily level, we do not include any time band FEs. Finally, we include traffic data for weekends, in addition to weekdays, and examine whether there are differential effects, as is common in the literature on congestion pricing (e.g., Timmins & Murdock 2007). We interact *SFparkPilot* with a dummy variable for weekends, which takes the value 1 for weekends and is 0 otherwise. In another specification, we consider the effects at blocks with new meters. Before discussing our results, we turn to evaluating the plausibility of the common trend assumption. Figure 4 shows weekly trends before and after SFpark was implemented for pilot (solid line) and control (dashed line) blocks, where the vertical line represents the week that overlaps with July 21, 2011, the date SFpark started. The trends for pilot and control blocks are similar prior to SFpark, suggesting that our estimates will not be biased upwards using a DiD framework.[14] Summary statistics for different measures of congestion are provided in panel B of Table 1.

Results of our regressions are presented in Table 3. Columns 1 and 2 of panel A present effects for lane occupancy, and we find SFpark had a negative, significant effect on weekdays of 5 percentage points (p<0.01), representing a very sizeable 29% of average daily lane occupancy. In view of the lack of significance of the interaction effect between *SFparkPilot* and weekends, the total weekend effect is significant and similar in magnitude to the weekday effect. We also observe impacts at blocks with new meters and find a positive, significant effect of 1 percentage point (p<0.01), indicating that relative to pilot blocks with prior metering, newly metered blocks experienced an increase in lane occupancy. Columns 3 and 4 of panel A present the effects of SFpark upon vehicle count. These results indicate a negative, but insignificant, effect on weekdays of 4 vehicles, or about 6% of the daily average weekday vehicle count, and a similarly insignificant effect at blocks with new meters. The total weekend effect is a larger and significant reduction of 7 vehicles, representing 12% of the weekend average vehicle count.[15].

The most plausible interpretation of our results is that there is less overall traffic in SFpark pilot blocks relative to control, most likely due to more turnover from parking and/or from reduced cruising, along with the observed substitution between automobile and bus transit. To better understand the possible mechanisms, we begin first with results from the weekends, where, due to

[14] We note that the regression approach to examining the plausibility of the common trend assumption used in §4.4 is not available here due to the lack of sufficient time periods prior to the commencement of SFpark (data from only one rate adjustment period prior to SFpark is available).

[15] On-street parking was free on Sundays in some parking management districts that included pilot blocks. Consequently, in a separate regression, we drop observations on Sunday, but results are similar to those in Table 3. More information on Sunday metering for on-street parking is available in section A.1 of the Appendix.

the much lower levels of congestion in general, one may more easily understand the key mechanisms. Our result showing a significant negative effect on lane occupancy on the weekends most likely reflects increased turnover at pilot blocks and consequently lesser cruising, confirming the findings of a previous study (Millard-Ball et al. 2014). Additionally, the reduced vehicle count we see on weekends also likely captures reflects this traffic volume. A similar interpretation also holds for results regarding weekdays, despite the smaller magnitude of effect, since lane occupancy and vehicle count are both reduced, though the latter finding is insignificant. In view of the very local spatial and fine temporal dimension of cruising, it is difficult to gain more insight from a reduced form analysis of daily data. In summary, our results suggest that not only are there are fewer cars on a given weekday and weekend, but also that they occupy less space in a given block.

Similar to the case of transit usage (in §4.3), we examine if there was any significant variation across different time periods, since the SFPark "treatment" was in effect varying every rate adjustment period. For similar reasons to the case of transit, we consider two treatment periods, 1 and 2, where treatment period 1 represents rate adjustment periods 1 through 5 and treatment period 2 includes rate adjustment periods 6 through 10. The results of these regressions are presented in Panel B of Table 3. For lane occupancy in columns 1 and 2, we find negative significant effects of about 5 percentage points in both treatment periods. For vehicle counts in columns 3 and 4, we find a significant negative effect in treatment periods 1 and 2 during the weekends, but only a negative significant weekday effect in treatment period 2, of about 6 percentage points.

We briefly turn to tracing the implications for congestion, the key question of interest in urban transportation. In view of both the reduced-form nature of our analysis and the daily nature of our data, quantifying the degree of congestion relief is infeasible, particularly since the relationship between traffic flow and congestion is complicated.[16] However, since the relationship between vehicle count and lane occupancy is non-linear, implying that a unit reduction in vehicle count can translate into more-than-unit reductions in occupancy (Anderson 2014), the larger, and significant, effects on lane occupancy strongly suggest that SFpark is associated with congestion-relief.

6. Environmental and economic benefits of SFpark

Unpriced externalities are arguably pervasive in urban transportation, with pollution and congestion being the most important ones. Given the strong interconnections between different aspects of transportation or the “markets” for different transportation services such as roads, fuel, parking and pollution, correcting one externality may either alleviate or exacerbate others (e.g. Bento et al. 2014). More specifically, it has been argued that private parking is significantly underpriced, in view of the many externalities exerted in the market for parking (Shoup 2011). In consequence, parking policies resulting in shift of mode away from private automobiles or alleviating parking-related congestion are likely to lead to indirect (“ancilliary”) benefits in terms of reduction in externalities. Given that SFpark and other smart parking programs are neither targeted at some of these externalities nor do they involve particularly sizeable changes in parking prices or other transit-related infrastructure, the size of these ancillary benefits is interesting to evaluate. To the extent these are sizeable, there is an additional impetus to other cities contemplating such programs, and enlarged benefits of changing current ways of managing under-priced public resources.

[16] We note that congestion reduction is not directly implied by a reduction in either vehicle count or lane occupancy on its own (e.g. a reduction in one or the other can in fact imply increased traffic congestion). However, when both are reduced, as in our case, congestion reduction is most likely to follow. See the discussion in §4.4 of Anderson, 2014 for an applied illustration, and Small and Verhoef, 2007 for a detailed discussion.

To this end, we quantify the environmental[17] and economic benefits arising from SFpark, focusing on the avoided pollution and avoided congestion-related costs. We begin with avoided pollution first, noting that the premise of our computation is that additional bus transit usage would not have occurred absent SFpark; these passengers, consequently, would have generated additional vehicle miles travelled (VMT), leading to additional emissions. In common with prior studies imputing such avoided costs as benefits (e.g., Currie et al. 2009, Ngo 2017), we compute the value of these avoided emissions from existing sources relevant for San Francisco.

Our results in §4 suggest that individuals switch from auto to transit usage during the SFpark pilot evaluation period. This is further reinforced by our results in §5 which show a decrease in vehicle count during the same period. According to a study by the Brookings Institution (2015), the average commuting distance within the larger San Francisco metropolitan area is 8 miles. We use half this distance (4 miles) since we are most interested in the city of San Francisco only, where travel demand is likely a mix of commuting and other shorter distance trips, as opposed to the larger metropolitan area. We multiply this commute distance by 21.1, which is the result in column 1, row 1 of Table 2 and represents the change in transit ridership following SFpark at pilot blocks on weekdays per time band. We then multiply this number by 4.4, which represents the reduction in vehicle miles travelled (VMT) per one passenger-mile on transit in San Francisco (Metropolitan Transportation Commission (2010), Holtzclaw 2018). This yields the number of VMT reduced due to SFpark. We then estimate the savings from reduced pollution due to lower VMT following SFpark, focusing on the four major pollutants: volatile hydrocarbons (VOCs), nitrogen oxides (NOx), carbon monoxide (CO), and carbon dioxide (CO_2). Details of

[17] The lack of adequate number of air pollution monitors (there is only a single pollution monitor in the city of San Francisco) is the major cause of not using observed pollution measures. Given that traffic emissions decrease exponentially within a few hundred feet of the source, using pollution data from this single monitor is likely to dramatically underestimate changes in pollution levels from changes caused as a result of SFpark.

these calculations are presented in §A.3 of the Appendix. Based upon these computations, we estimate the benefits of avoided pollution at \$14.33 on an average SFpark census block for a given time band, date and rate adjustment period on weekdays. Scaling up to the time-band level for all 234 blocks included in the SFpark pilot evaluation program leads to an estimated saving of \$4 million. More details about these calculations are in the Appendix, section A3.

Next, following interest in the recent literature in valuing congestion relief (e.g. Anderson 2015; Gibson and Carnovale, 2015), we also provide an estimate of the purely economic benefits of congestion relief provided by SFpark. Congestion is an aspect affected by many different factors, only one of which is parking-induced externalities such as cruising. Congestion relief can provide many benefits, including pollution reduction, increased economic values both because opportunity costs are non-trivial during peak periods and since individuals experience significant disutility from congestion-imposed delays. Since the pollution effects of a shift to transit is already accounted for, we focus on the economic value loss avoided consequent to reduced congestion. We consider the most common solution to congestion: pricing driving during peak hours, and we focus on arterial roads. San Francisco-specific figures for optimal congestion pricing, the point at which the value of each trip to an individual is at least as large at the social cost of the trip, are provided by the U.S. Department of Transportation (2009), which suggests a toll, based purely upon the value of time, of 23 cents per mile. Using the VMT avoided of 141.01 million leads to congestion-related benefits of **\$32.43 million** over the duration of the SFpark pilot project. This estimate likely undervalues the congestion-related benefits, excluding as it does the additional value of time spent in transit, including cruising.

It is instructive to assess these benefits against the cost of SFpark during a similar period, to obtain an idea of the possible magnitude of welfare increases. Similar to the case of welfare gains, we focus exclusively on the pilot evaluation period for computing costs. Data from these parking sensors were collected between April 1, 2011 to June 30, 2013 for control areas and until December 31, 2013 for the pilot areas. Parking sensors cost $330 to install per parking space and $10 per month and space thereafter and covered 8,200 spaces (SFMTA 2014a). Assuming all spaces operated for 33 months between April 2011 and December 2013, this suggests a total cost of $5.4 million. While these estimates represent the low-end of costs (since there are other costs toward overhead, managing the program, and installing new or updating parking meters) they provide a baseline to evaluate net benefits within the limitations of the information publicly available. These figures suggest substantial net benefits of the SFpark pilot project, to the extent of $31 million. In fact, gains from avoided pollution are themselves sufficient to cover a sizeable part of the costs of the evaluation project. In view of the high fixed cost of installing these sensors and initiating SFpark, the small marginal cost of maintaining the sensors and perhaps other technology used for SFpark suggests the net benefits of SFpark is likely to increase over time. We emphasize that our heuristic assessment of costs and benefits are not intended to account for the full range of benefits a project such as SFPark is likely to lead to. The finding that avoided pollution and congestion costs are, by themselves, more than sufficient to cover the costs for a program such as SFpark, however, suggests that simple measures such as these can help partly mitigate some of the externalities involved in urban transportation.

7. Conclusion

In this study, using the quasi-natural experiment nature of a demand-responsive parking pricing program in San Francisco city, SFpark, we examine its effects upon on transit usage and traffic flow. Our results regarding transit usage suggest a statistically significant increase in ridership in SFpark pilot blocks, varying between 10 and 21 depending upon the type of control blocks used. In addition, there is some evidence of re-optimization over the different rate adjustment periods, where drivers learn about aspects of SFpark, with the more optimized effect smaller than the short-run effect. They also suggest a very reasonable temporal substitution pattern: reduction in transit usage during the off-peak afternoon period (12 noon-3 PM), which may be commensurate to an increase in auto usage during those times. We emphasize that prior studies have focused on the stated goal of SFpark, rationalizing occupancy. Our findings, of a reasonably large increase in transit usage, indicate that SFpark exerted a rather important additional effect. This finding is particularly interesting in view of both the rather modest, on the whole, changes in price involved and because effecting modal shifts was not a goal of SFpark. We also find a reduction in both vehicle count and lane occupancy, indicating a decrease in traffic volume and implies a reduction in congestion. The increase in transit usage and reduction in vehicle count, together suggest the most plausible explanation is that SFpark led to a mode switch from auto to transit usage. While prior theoretical literature on parking discussed the link between congestion and parking, our analysis is the first, to our knowledge, to provide rigorous empirical evidence to this effect.

Our findings provide some supporting evidence for two distinct hypotheses related to different aspects of urban transportation. This first is that public transit and road pricing are substitutes, an aspect explored most recently in Gibons and Carnovale (2015) in the context of congestion pricing. In our particular instance, the form of road pricing considered is on-street parking pricing. It also provides evidence for a second hypothesis, that parking pricing helps ameliorate many externalities in transportation. In this connection, our results indicate that, in just the two years of the pilot project, the avoided pollution benefits alone are sufficient to cover a large part of the costs of the project, with the project generating net benefits of about $31 million.

Our results have many policy implications. They suggest that policy makers and transportation planners interested in reducing traffic-related externalities should consider appropriately pricing on-street parking, since not only have studies shown it can increase turn over and reduced cruising, but also affect shifts in modal choice towards transit. In addition, they also imply that the goals outlined in SFMTA's strategic plan for 2013 to 2018, which aims for 50% of trips to use private automobiles and 50% trips to use non-private auto modes including public transit (SFMTA 2017), may be aided by rationalized parking charges. While our findings relate directly to San Francisco, given that many cities share key characteristics, including increased population-related traffic increases and the presence of good quality public transit options, the insights obtained here should be broadly applicable to many urban agglomerations both in the U.S. and elsewhere. In addition, they also suggest that even in cities with relatively well developed transit systems, pricing leads to some amount of traffic reduction.

Our study provided novel empirical evidence regarding the different dimensions of benefits of rationalizing road (here, parking) pricing. Nonetheless, many relevant aspects remain unexplored, including: questions related to the degree of congestion relief provided; pollution reduction experienced and its spatial patterns; and the elasticity of different aspects of road pricing.

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FIGURES

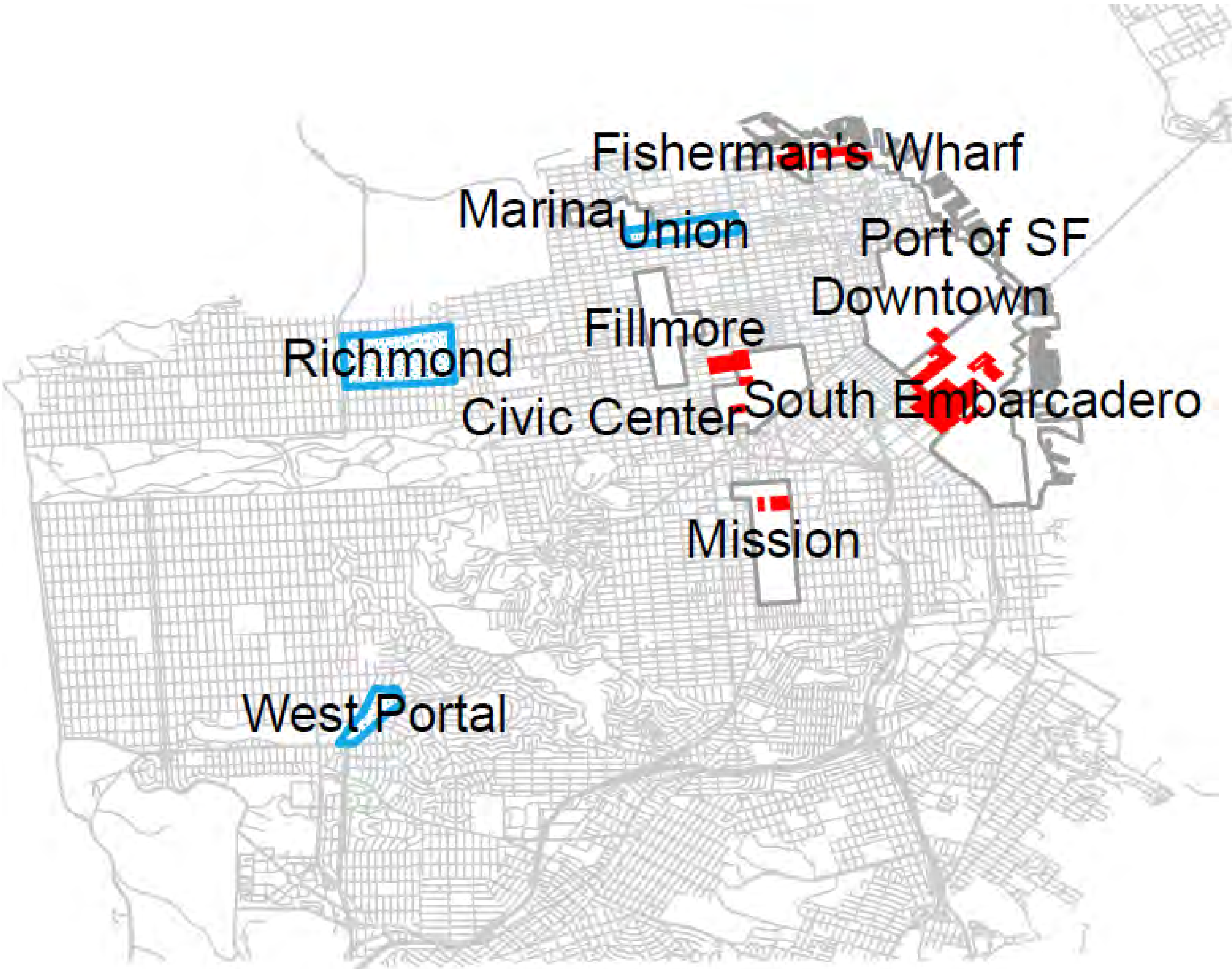

Figure 1. This map shows streets in San Francisco, the census blocks with newly installed meters (red), and the parking management districts involved in the SFpark pilot evaluation. The control parking management districts include West Portal, Richmond, and Union (dotted and outlined in blue), however due to the unreliability of data in West Portal, we dropped this parking management district from our study. The pilot parking management districts include Fisherman's Wharf, Marina, Port of SF, Downtown, Fillmore, Civic Center, South Embarcadero, and Mission.

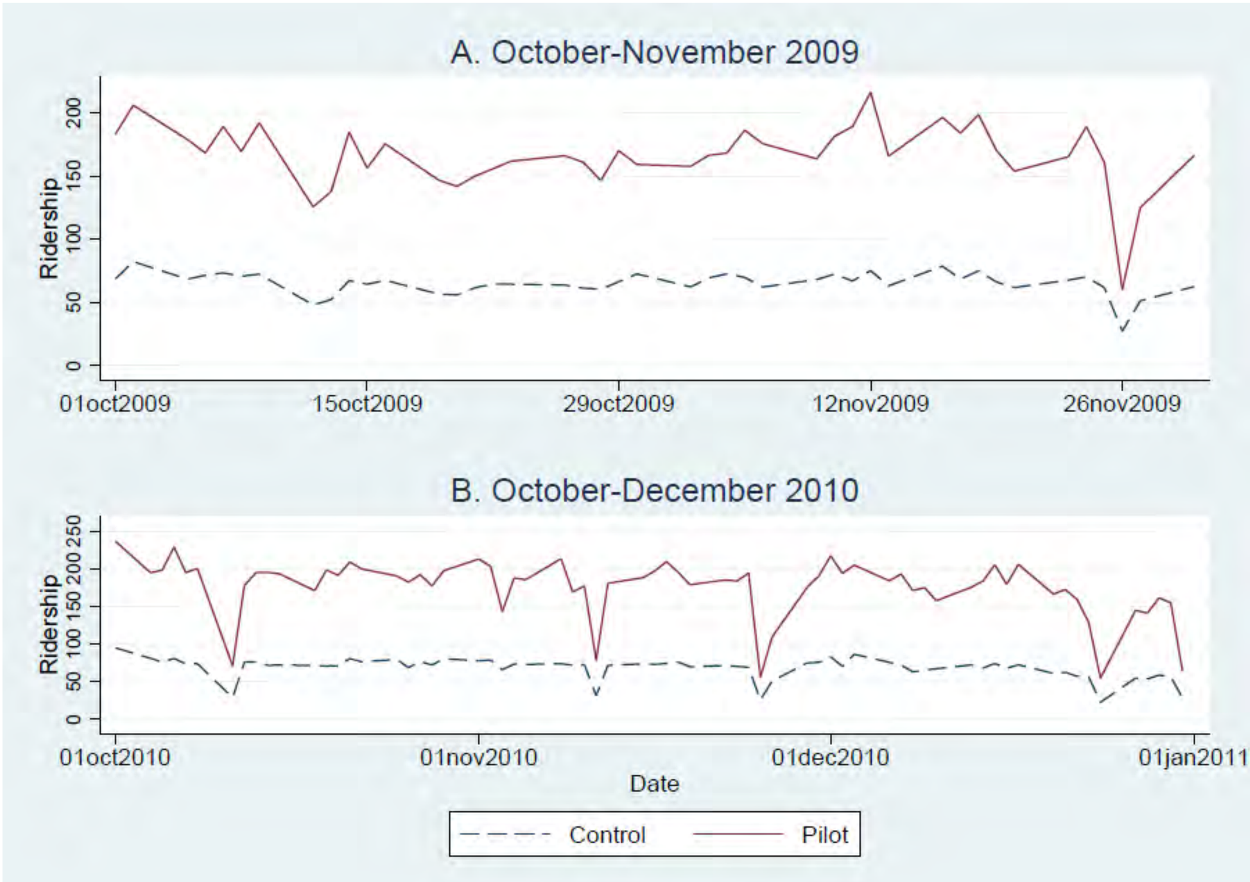

Figure 2. Graph of pre-SFpark average daily ridership between October and November for 2009 and October to December for 2010. We drop observations for weekends and federal holidays. The control blocks (dashed line) have a lower ridership compared to pilot blocks (solid line), but trends are similar over time prior to SFpark.

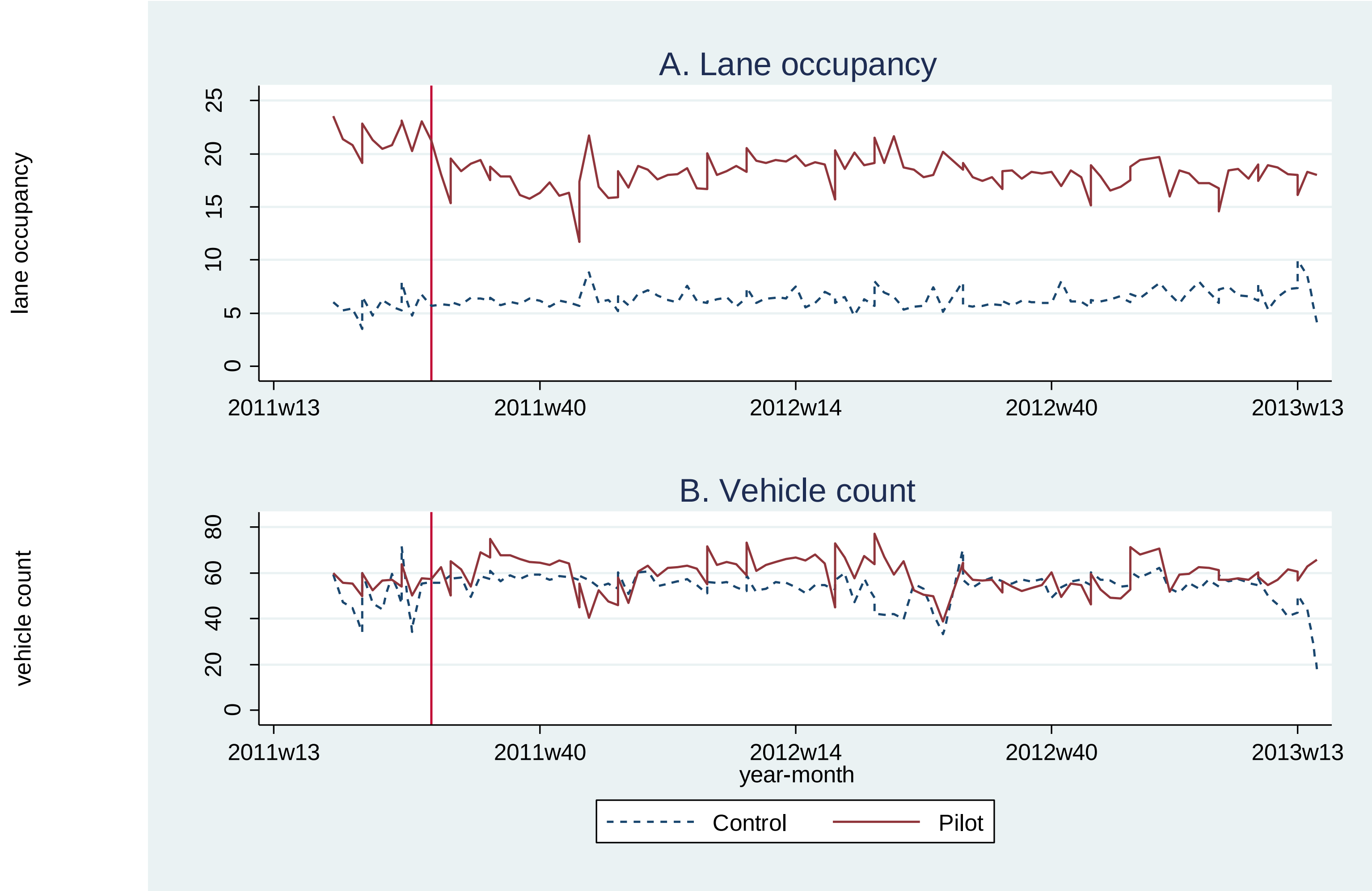

Figure 3. Graph of the average monthly percentage of time a car was detected above the sensors (lane occupancy), average vehicle count and average speed using data from the SFpark pilot evaluation data between May 2011 and April 2013 for control (dashed line) and pilot (solid line). We drop federal holidays and weekends. The vertical line represents July 2011, when SFpark started. This graph shows similar trends for pilot and control blocks prior to SFpark.

TABLES

Table 1. Summary statistics for the dependent variables for weekdays

	N	Number of census blocks	Mean	Std deviation
Panel A: Number of people embarking and disembarking at bus stops within 500 ft of census block for a given time band and date				
All blocks	4,101,412	5,304	76	156
SFpark Pilot blocks	171,333	234	185	241
SFpark Control blocks	31,917	37	108	135
Other control blocks	3,898,162	5,033	71	149
SFpark Pilot blocks- new meters	13,969	36	155	262
Time band 1 (7am to 12pm)	1,045,851	1,538	107	209
Time band 2 (12pm-3pm)	1,005,362	1,296	64	131
Time band 3 (3pm-6pm)	1,039,082	1,487	80	154
Time band 4 (after 6pm)	1,011,117	1,314	53	100
Panel B: Daily traffic measures for SFpark pilot evaluation blocks				
Lane occupancy (All)	59,340	109	18	21
Weekday	46,903	109	18	21
Weekend	12,437	109	17	20
SFpark Pilot blocks	54,162	100	19	22
SFpark Control blocks	5,178	9	6	3
SFpark Pilot blocks- new meters	5,241	7	16	16
Average vehicle count (All)	59,340	109	61	47
Weekday	46,903	109	62	48
Weekend	12,437	109	57	43
SFpark Pilot blocks	54,162	100	62	49
SFpark Control blocks	5,178	9	54	16
SFpark Pilot blocks- new meters	5,241	7	49	25

Notes: The SFpark Pilot and Control blocks represent blocks part of the SFpark pilot evaluation. The “SFpark Pilot blocks- new meters” represent blocks that have newly installed meters as a result of SFpark. “Other control blocks” in Panel A represent all other control blocks in San Francisco with a bus stop that were not part of the SFpark pilot evaluation.

Table 2. Impacts of SFpark on transit ridership using equation (1) in San Francisco on weekdays

	1	2	3	4	5	6	7	8	9
	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark
SFparkPilot	21.1***	20.2***						17.7***	17.1***
	[5.10]	[5.17]						[5.04]	[4.97]
SFparkPilot*new meters		9.49		10.3			11.9		10.1
		[21.7]		[21.8]			[21.9]		[30.1]
SFparkPilot*treatment period 1			29.7***	28.8***	34.2***				
			[6.33]	[6.13]	[6.90]				
SFparkPilot*treatment period 2			10.4**	9.40*	17.2***				
			[4.56]	[5.06]	[4.98]				
SFparkPilot*treatment period 3					10.4**				
					[4.56]				
SFparkPilot*time block 1 (7am-12pm)						70.9***	72.6***		
						[10.9]	[11.6]		
SFparkPilot*time block 2 (12pm-3pm)						-22.9**	-21.1**		
						[9.20]	[9.89]		
SFparkPilot*time block 3 (3pm-6pm)						27.5***	29.3***		
						[8.77]	[9.64]		
R2	0.092	0.092	0.092	0.092	0.092	0.096	0.096	0.091	0.091
N	4,101,412	4,101,412	4,101,412	4,101,412	4,101,412	4,101,412	4,101,412	4,087,213	4,087,213
Number of census blocks	5,304	5,304	5,304	5,304	5,304	5,304	5,304	5,281	5,281

Note: * p<0.10 ** p<0.05, *** p<0.10. Robust standard errors are clustered at the census block. Each column represents a separate regression. The dependent variables is the total number of people who embark and disembark at bus stops within 500 ft of the centroid of a census block. These data only include rate adjustment periods 2, 3, 7 and 8. The Muni bus transit data are at the time band-census block level using equation (1). Columns 8 and only account for blocks where at least one part of the block started on the initial start date of SFpark, July 21, 2011

Table 3. Impacts of SFpark on average daily measures of traffic flow on weekdays and weekends

	1 Lane occup	2 Lane occup	3 Vehicle count	4 Vehicle count
Panel A: DiD baseline model				
SFparkPilot	-5.20***	-5.25***	-4.1	-4.09
	[1.83]	[1.84]	[2.87]	[2.88]
SFparkPilot*weekend	-0.1	-0.11	-3.21***	-3.21***
	[0.37]	[0.36]	[0.86]	[0.86]
SFparkPilot*new meters		1.12**		-0.14
		[0.44]		[0.60]
Total weekend effect	-5.31***		-7.31**	
R^2	0.073	0.073	0.067	0.067
Panel B: 2 treatment periods				
SFparkPilot*treatment period 1	-5.16***	-5.21***	-4.16	-4.15
	[1.84]	[1.84]	[2.92]	[2.93]
SFparkPilot*treatment period 2	-5.22***	-5.28***	-5.74**	-5.73**
	[1.82]	[1.83]	[2.70]	[2.72]
SFparkPilot*treatment period 1*weekend	-0.3	-0.31	-2.45**	-2.45**
	[0.38]	[0.38]	[0.98]	[0.97]
SFparkPilot*treatment period 2*weekend	0.05	0.043	-3.82***	-3.82***
	[0.37]	[0.37]	[0.89]	[0.89]
SFparkPilot*new meters		1.13**		-0.15
		[0.44]		[0.60]
Total weekend effect (treatment period 1)	-5.46***		-6.61**	
Total weekend effect (treatment period 2)	-5.17***		-9.56***	
R^2	0.073	0.074	0.067	0.067
N	59,340	59,340	59,340	59,340
Number of census blocks	109	109	109	109

Notes: * p<0.10 ** p<0.05, *** p<0.10. Robust standard errors are clustered at the census block. We use equation (1), but substitute parking management district-year trends for neighborhood year trends, since a parking management district is the more appropriate aggregation at which factors that influence parking vary. Each column and panel represents a different regression. Also, since we only have congestion data at the daily level, we do not include any time band FEs. The total weekend effect is the sum of the coefficients on *SFparkPilot* and *SFparkPilot*weekend*.

APPENDIX

Figure A1. Example of parking block faces assigned by SFpark (green lines) and census blocks from the 2010 U.S. Census (black lines).

Note: In some cases, the SFpark block faces overlap more than 1 census block. Since we do not have block id numbers for all block faces but only for block faces with SFpark pilot and control groups, we aggregate data to the census block level. While some block-faces easily correspond to census blocks because these block-faces fall "completely inside" a census block, other block-faces are harder to characterize since they may span several census blocks, as demonstrated in the figure. Of the 2,715 block-faces that include pilot and control blocks as part of SFpark, 369 blocks cross one or more census blocks. We discuss how we merge these data with transit bus data further in the text (see 3.3).

Figure A2. This figure shows streets in San Francisco and the census blocks with at least one SFpark pilot (black) or control (yellow) block face as part of the SFpark pilot evaluation. The dots represents the locations of bus stops in San Francisco. For our regressions examining impacts on transit usage, any block not part of the SFpark pilot evaluation that included a bus stop was included as a control block. There are 540 census blocks with at least one pilot block face and 61 census blocks with at least one control block face from the SFpark pilot evaluation. However, there are only 234 census blocks with both a bus stop and pilot block face and 37 census blocks with a bus stop and a control block face from the SFpark pilot evaluation. There are 7386 census blocks using the 2010 census blocks in San Francisco.

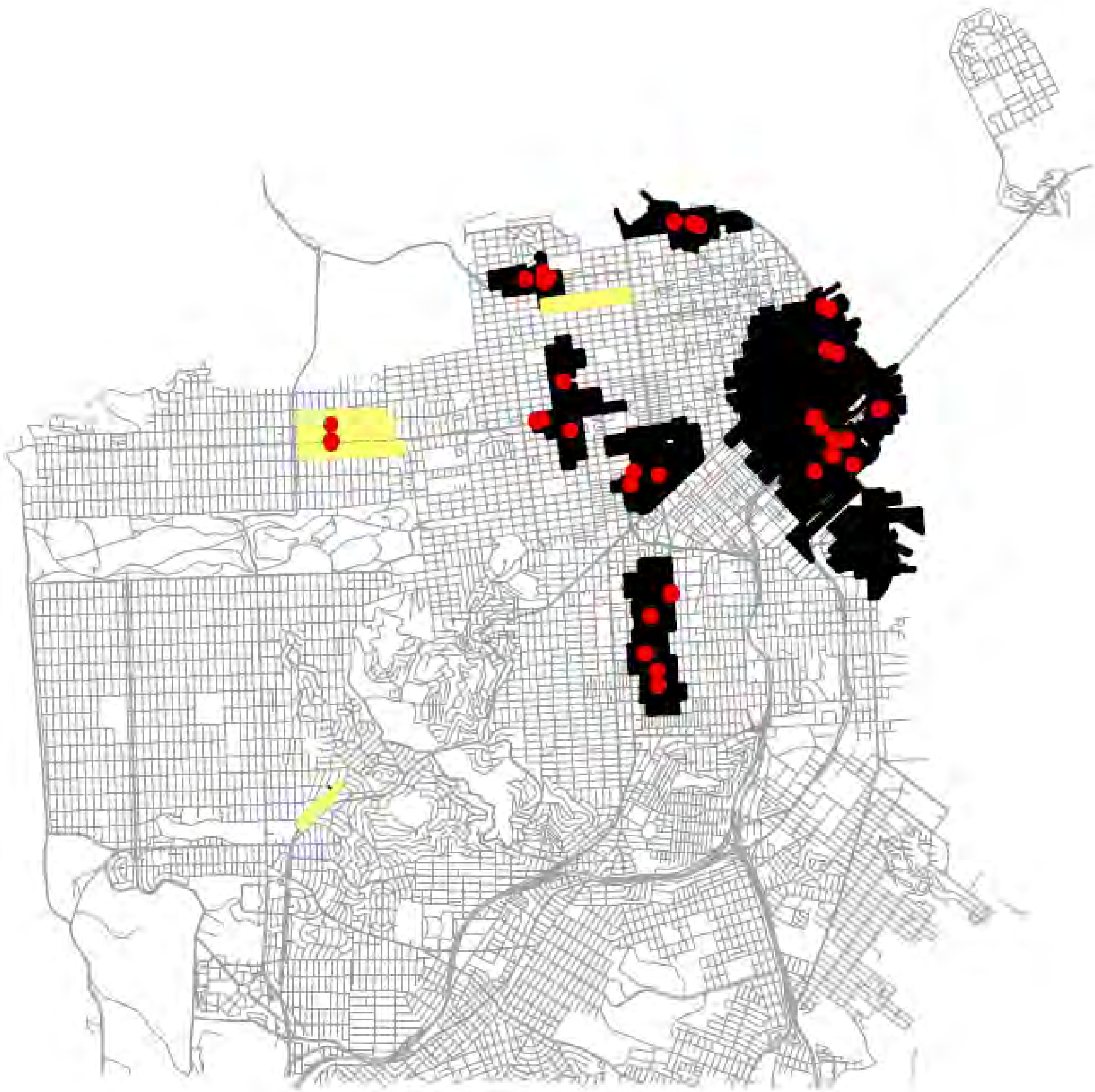

Figure A3. This figure shows streets in San Francisco and the census blocks with at least one SFpark pilot (black) or control (yellow) block face as part of the SFpark pilot evaluation. The dots represents the locations of roadway sensors along pilot and control blocks as part of the SFpark pilot evaluation. For our regressions examining impacts on congestion, we only use blocks part of the SFpark pilot evaluation.

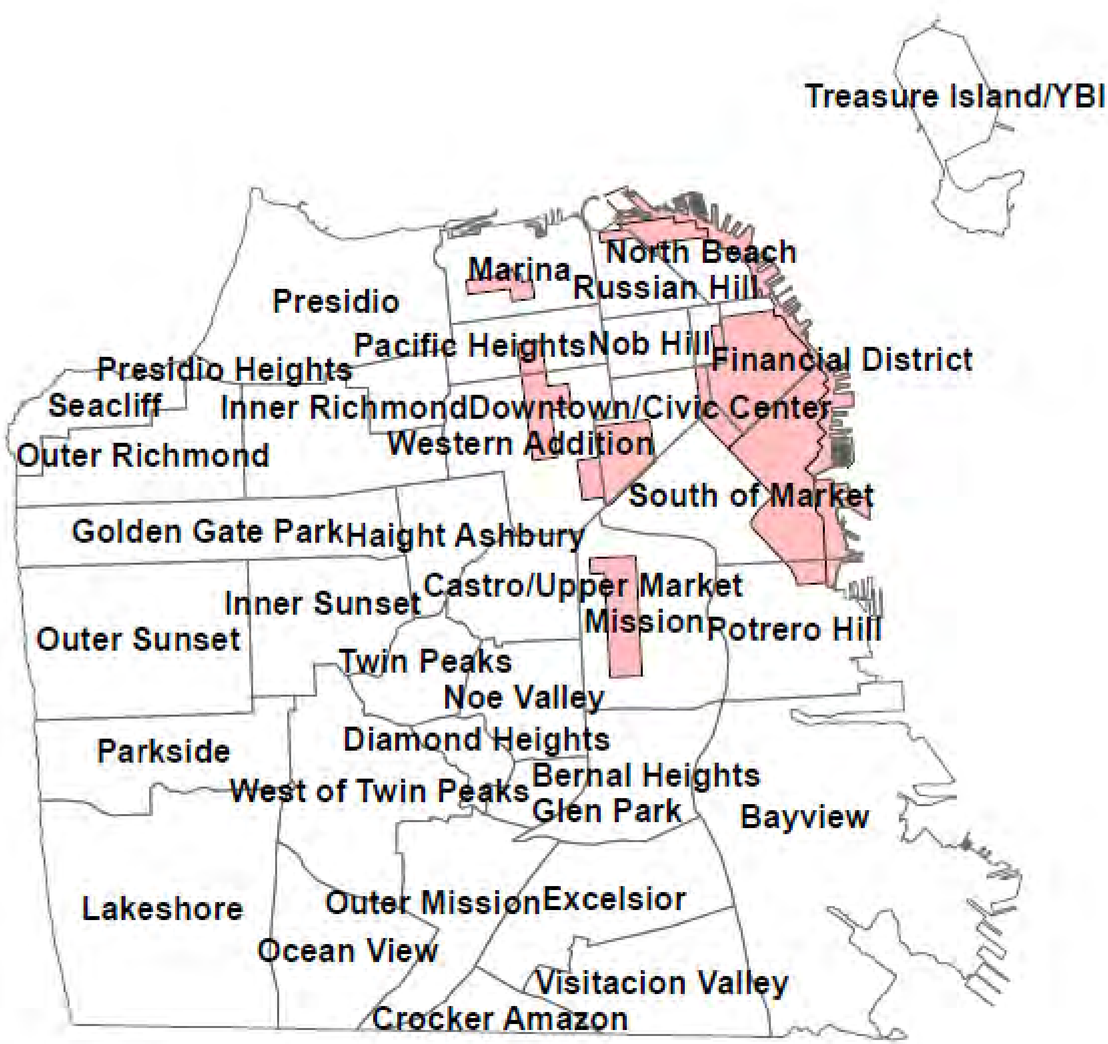

Figure A4. This figure shows the different neighborhoods in San Francisco and the coloured areas show where the SFpark pilot blocks occurred.

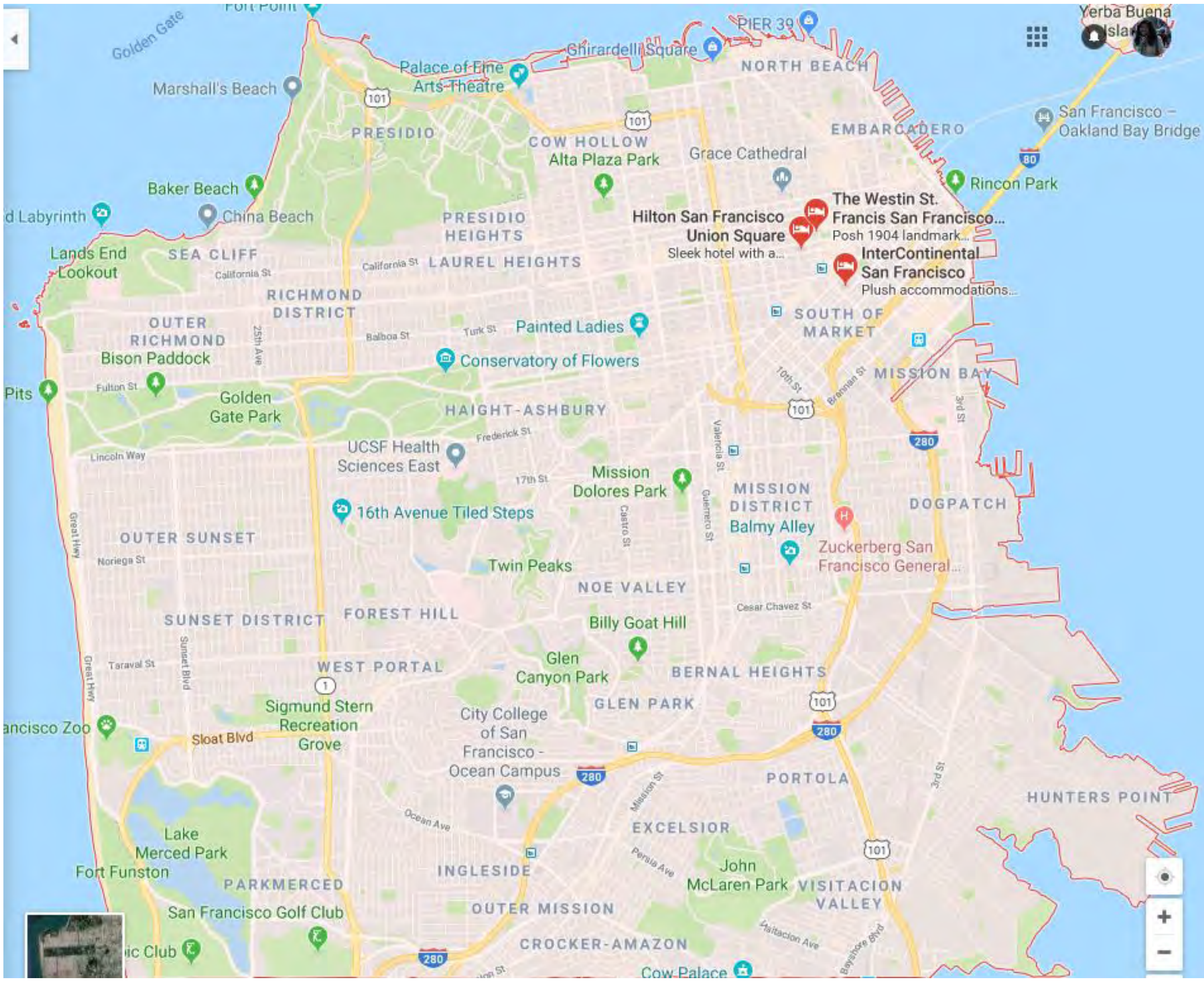

Figure A5. This map shows the different highways and freeways in San Francisco in addition to the neighborhoods. Source: Google Maps

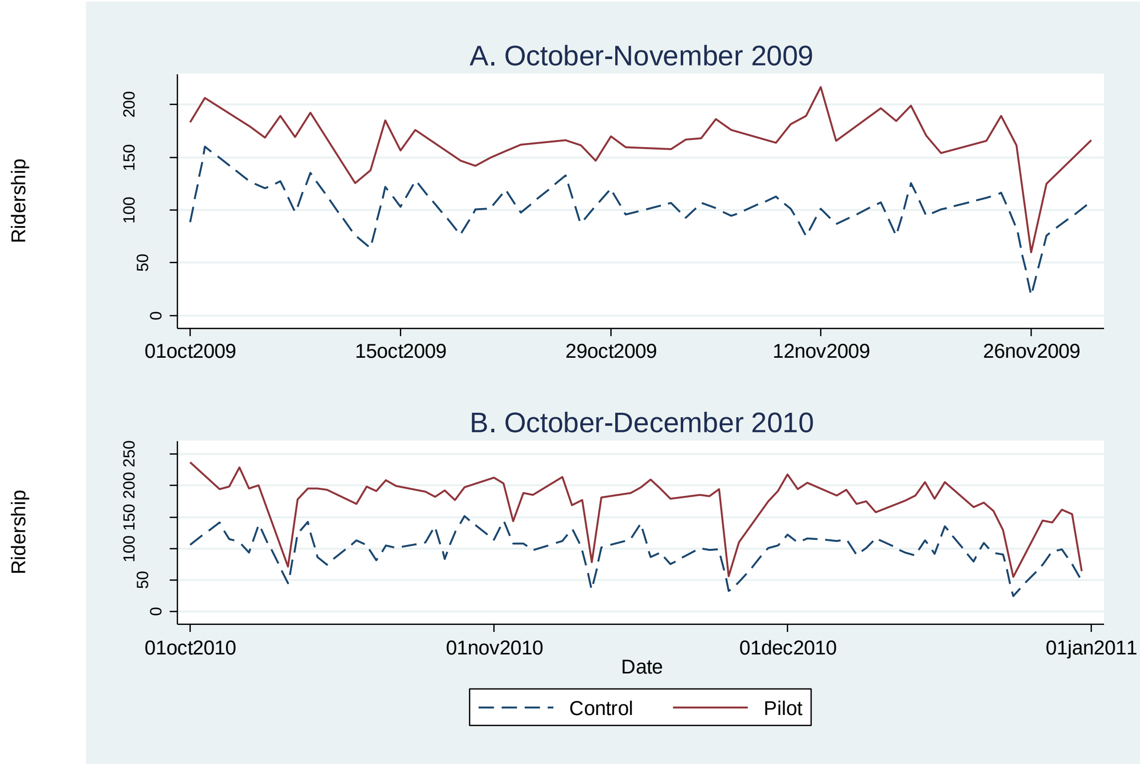

Figure A6. Graph of pre-trends for SFpark control and pilot blocks part of the SFpark pilot evaluation only.

Table A1. Impacts of SFpark on transit ridership using equation (1) using SFpark pilot evaluation census blocks only

	1	2	3	4
	Embark and disembark	Embark and disembark	Embark and disembark	Embark and disembark
SFparkPilot	9.67**	9.02**	8.44*	7.75*
	[4.36]	[4.22]	[4.47]	[4.29]
SFparkPilot*new meters		14.5		21.3
		[19.4]		[31.8]
R2	0.213	0.213	0.213	0.213
N	203,250	203,250	189,051	189,051
Number of census blocks	281	281	258	258

Notes: * $p<0.05$ ** $p<0.01$. Robust standard errors are clustered at the census block. We use equation (1), but only include pilot and control blocks part of SFpark's pilot evaluation in case these blocks are systematically different from blocks that were not chosen to be part of SFpark's pilot evaluation. Columns 3 and 4 show results for blocks where at least one block face started SFpark on July 21, 2011. For more information, see notes for Table 2.

Table A2. Test of the common trend hypothesis

	1 Embark and disembark	2 Embark and disembark
Pilot*rate adjustment period	-6.36***	-5.44**
	[1.72]	[2.30]
Rate adjustment period	8.88***	51.0***
	[0.53]	[5.78]
R2	0.093	0.203
N	2,028,557	116,630
Number of census blocks	5,289	281
Sample	FULL	SFpark Blocks only

Notes: * p<0.05 ** p<0.01. Robust standard errors are clustered at the census block. There are 5,178 census blocks. We use equation (1), but only include observations prior to SFpak. Instead of the variable *SFpark*, we our independent variable of interest is an interaction between a dummy variable for pilot blocks and a rate adjustment period trend, which represents changes in transit ridership across approximate 8-week rate adjustment periods before SFpark. We also include a rate adjustment period trend, and the remaining control variables in equation (1). The number of census blocks is 13 blocks less than the number of census blocks in Table 2. This could be due to the addition of bus stops from prior to after SFpark. Given the difference represents 0.2% of census blocks, we are not concerned about possible issues of bias. Additionally, the increase in census blocks is unlikely correlated with the timing and location of SFpark's implementation.

A. More information on SFpark and Muni bus data

A.1 SFpark data

Data were obtained from SFpark's "Parking Sensor Data Guide" (found here: http://sfpark.org/resources/parking-sensor-data-guide/) and from e-mail exchanges with Prof. Millard-Ball. The original data set had 7,902,290 observations but a significant number were dropped to ensure that data met specific requirements. For example, we dropped 4,850,187 observations when meters were not operating, since the greatest effects will occur during metered times. We also dropped 54,072 observations in the parking management district of West Portal, which only included control blocks, since these observations were considered unreliable (p. 16). Next, we dropped 11,304 observations in the California and Steiner Lot, which included only pilot blocks, since we were most interested in on-street parking. We then dropped 37,541 observations for blocks at two streets, Howard St. 0 and Spear St. 400, since these streets had different meter rates for the same date and time of day. We dropped 1 observation which did not list if it was a control or pilot block and dropped 27,709 observations between December 10-17, 2012 on the advice of Prof. Millard-Ball. Additionally, the start date of the first rate adjustment period differed for some blocks, where 89.9%, or 347 block faces, started on July 12, 2011, 7.8% started in August of 2011 and 2% started in late September or early October of 2011. All control blocks are in the parking management districts of Inner Richmond and Union. All pilot blocks are in Civic Center, Downtown, Fillmore, Fisherman's Wharf, Marina, Mission, and South Embarcadero.

We identified blocks with newly installed meters that were part of the SFpark pilot group using the following information. As part of SFpark, "SFMTA introduced new meters in several areas inside and outside of SFpark pilot and control areas in 2011. These newly installed meters resulted in a dramatic improvement to parking availability. Prior to installing meters, these blocks were too full 90% of the time. After the installation of meters, this figure dropped to just 15% of the time" (SFMTA, p. 70). Based on archived SFMTA press releases in 2010, some of the pilot blocks correspond to the proposed installation of approximately 1300 meters (SFMTA 2014b). We believe these blocks are part of the newly installed meters proposed by SFMTA that became part of SFpark for a couple reasons. In these archives, SFpark is not explicitly measured as the reason for installing these new meters, though a big motivation for installing new meters was because SFMTA was introducing “next-generation smart parking meters that accept credit cards, coins and the SFMTA parking card to make payment as convenient as possible," which essentially describes the objectives of SFpark. Any blocks with new meters that do not correspond to pilot blocks in SFpark were not considered. We then find if these proposed blocks correspond to pilot blocks using the SFMTA hourly data. Based on this method, out of 2715 blocks part of the SFpark pilot group, we found 50 blocks where meters were newly installed.

Additionally, starting January 6, 2013, or toward the end of our study period, SFMTA implemented metered on-street parking on Sundays between 12pm and 6pm in select areas as an experiment, whereas before parking on Sunday in most areas was free. The introduction of Sunday metered on-street parking took place in Mission, Marina, Union, Hayes Valley, Civic Center, Fillmore, and Richmond. This included pilot and control blocks, where demand responsive pricing was used in pilot blocks and traditional flat meter rates were used in control blocks. On-street parking was already metered in Downtown, Fisherman’s Wharf and South Embarcadero.

A.2 Merging Muni transit bus data with SFpark data

We generate a novel panel data set and merge Muni bus data with SFpark data. SFpark data are at the block face level, which is different than the census block since parking occurs on the sides of streets. Also, in some cases one block face can span more than 1 census block (Figure 2), so we aggregate SFpark data to the census block level. Of the 2,715 block faces that include SFpark pilot and control blocks, 369 blocks cross one or more census blocks. We merge these data with information on bus stops within 500 ft of the centroid of each census block level using a GIS map. We then merge these data with the Muni bus data, which are aggregated to the census block and time-band level since this is the level of variation of interest. Since we only have Muni bus data for certain parts of the year, observations for both SFpark and bus data overlap for October to December 2009 and 2012. This includes periods prior to SFpark and rate adjustment periods 2, 3, 7 and 8 after SFpark was implemented in 2011. While the lack of data for rate adjustment periods 4-6 may lead to reduced variability, our wide geographic coverage, and suggestive evidence for larger effects early on in SFpark , both indicate that if anything, our estimates may under-estimate the overall effect of SFpark on transit. We also focus on weekdays only, since this is the period where on-street parking will most likely be heavily utilized and affected, and exclude federal holidays for a similar reason. Summary statistics for transit bus ridership are in panel A of Table 1.

A.3. Details of calculations used to estimate pollution costs

Small and Kazimi (1995) estimate the cost of VOCs and NOx to be \$0.012 and \$0.015 per mile (resp.). We multiply the total reduction of 371 VMT by these costs and find savings of \$4.45 and \$5.57 for VOCs and NOx (resp.). For CO and CO_2, we could not find air pollution costs associated with VMT, so we first estimate reductions in total CO and CO_2 resulting from this switch between cars and buses, and subsequently quantify the value of this reduction. A study by the U.S. EPA (2000) estimates that emission rates of CO and CO_2 per mile for a passenger car is 20.9 grams (g) and 0.92 lb (resp.). We multiply this by 371 VMT, which shows the total reductions in CO and CO_2. We then use prices from the literature to assess the savings from these reductions. One study from Canada estimates the cost of CO to human health is $205 per ton and Ludlow et al. (2015) forecasts the price of CO_2 in 2020 will be $15 per ton, which is at the lower end of prices (Victoria Transport Policy Institute 2011). After converting units into tons, this suggests savings of $1.75 and $2.56 for CO and CO_2 (resp.).

To estimate the economic benefits from congestion relief for the ten rate adjustment periods during the pilot evaluation period, we assume approximately 40 weekdays per 8-week rate adjustment period and the figure of $14.33 is scaled up by 40*10*3=1200. This yields the figure of $16,800 per SFpark pilot block. With 234 pilot blocks, this yields a total benefit of $3.93 million. Note that we only consider three time blocks since, while there are 4 time bands, many blocks meter for only 3 time bands between 7am and 6pm

A.4 Details of calculations for congestion benefits

The total avoided VMT is computed thus: using, for reasons already outlined, the figure of 4 miles as the average distance travelled by a transit passenger, we arrive at a figure 372 VMT per time band, working day and pilot block. This is multiplied by the number of time bands (3); the number of working days over the duration of the pilot project i.e. between April 1, 2011 and June 30, 2103 (about 540); and the number of pilot blocks (234), yielding the total used above, 141.01 million.

We also assume that all of the reduction occur during the peak; and all lead to congestion relief. Clearly, not only is the first a reasonable assumption (in the absence of hourly congestion data), but also explicitly indicated by differentiated parking pricing during different time-bands, pre- and post-SFpark. The second one logically follows from the first, and is also supported by the finding of substantial increase in transit passengers during the peak, and a very moderate reduction during the off-peak (as indicated by the time-band-specific transit regression results in columns 8 and 9 of Table 2). Also, as already detailed (see footnote 13), arterial roads predominate in the regions of SF covered by the pilot project. Consequently, we use the lower congestion value figures for arterial roads, rather than the far higher one for freeways (29 cents).