Economic Impact of Smart Parking Meters on San Francisco *

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Abstract

This paper investigates the impact of high-tech equipment integrated with big data systems on urban planning and economic growth. In 2015, the U.S. Department of Transportation introduced the Smart City Challenge to support and incentivize mid-sized cities nationwide to upgrade their infrastructure. San Francisco City, one of the seven finalists, used part of the funds to expand SFpark, a "smart-parking" program, to the city's 28,000 on-street parking meters in early 2018. The primary objective of SFpark was to ensure that curb parking accommodates as many customers as possible for the adjacent businesses. By applying dynamic difference-in-differences methods, I find that SFpark positively impacts the growth rate in the number of businesses in the affected block groups. The positive effect is lessened in the area with a higher ratio of people and businesses per meter.

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1 Introduction

Smart cities are one of the significant breakthroughs in urban development. More than 80% of global GDP has been generated in cities, and smart technologies play a vital role in sustaining growth with higher productivity and innovation (Sharif, 2023). Such technologies can attract investment and improve the standard of living (Kamien and Schwartz, 1975). In 2015, the U.S. Department of Transportation initiated the Smart City Challenge as a leverage to promote the transportation system that integrated data, applications, and technologies. More than 78 mid-sized cities across the US participated in the challenge to upgrade their infrastructure systems.

Transportation networks, especially parking, are essential in urban planning. In large cities, parking operations have been a leading concern due to the increasing number of people and automobiles. A wide range of studies between 1927 and 2001 has estimated that parking "hunting" accounts for 30% to 50% of urban traffic. (Shoup, 2006). In congested areas, searching for a parking spot can impact the time customers spend shopping and the sales of businesses. Terrible parking management drives customers away or causes them to reduce the time they want to spend shopping; however, as shoppers spend less time in stores and parking spots become vacant, there is a potential for more shoppers to visit in a given time-frame (Hymel, 2014). In response, several cities such as San Francisco, London, Seattle, Berlin, Santiago, and Singapore have adopted and implemented "smart parking" to enhance traffic efficiency. In the downtown area, the dynamic pricing parking model emphasizes traffic optimality and indicates that on-street parking charges can be increased until the need for cruising for parking is eliminated (Arnott and Inci, 2006).

As the home of the world's most vivacious tech companies, San Francisco was one of the first cities to attempt demand-responsive parking. Beginning in 2011, the San Francisco Municipal Transportation Agency (SFMTA) initiated SFpark, a strategy aimed at increasing parking availability while reducing congestion and enhancing driver safety to improve parking conditions in the city. Roughly 80% of the SFpark project came from federal funding through the Department of Transportation's Urban Partnership Program. SFpark is a parking management system that controls and tracks the availability of both on and off-street parking (SFMTA, 2014). The main purpose is to reduce the time spent finding parking slots and cruising, thereby increasing the flow of other transportation, such as buses, trolleys, bikes, etc. Through a computerized "smart" system and sensor technology on each meter, SFpark can collect the occupancy with payment data. Based on the principle of supply and demand, this upgrade supports pricing adjustments for on-street parking to match demand block by block. SFpark also offers a free app that displays the real-time price with space availability, and users can pay for parking through the app. Compared with road pricing, dynamic parking pricing is more mico-scale and more effective in dense areas of the cities.

From 2011 to 2013, SFpark conducted experiments on its new project at 7,000 out of 28,000 metered spaces in San Francisco City. Lane occupancy fell by nearly 5% from mid-2011 to 2013, yielding the congestion-related benefits of $31.5 million along with other positive externalities such as the environment (Krishnamurthy and Ngo, 2020). The city achieved its goal of 60% - 80% occupancy and decreased cruising by nearly 50% over the same duration of the SFpark pilot project (Hampshire et al., 2014). According to earlier reports, SFpark program modified parking prices at least ten times, and the on-street SFpark offered an average parking rate of 4% lower.(SFMTA, 2014).These achievements allow for the cheaper pricing adjustment of parking fees, accommodate more traffic flow, and thereby affect business sales through the shopping experience (Hymel, 2014). There may be a correlation between the increased business entry rates and the presence of smart parking meters. The lower parking fees and improved traffic management introduced by SFpark could influence the operations of local businesses.

In late 2015, San Francisco participated in the Smart City Challenge, and the SFpark project was the key proposal in their application. As one of the seven finalists, San Francisco received an $11 million grant from the U.S. Department of Transportation to invest in their high-tech infrastructure, such as Smart Carpool Pilot and Smart Traffic Signals. In early 2018, the SFpark program was approved by San Francisco City and expanded the system to the entire city's 28,000 on-street meters. The goal of expanding SFpark is to increase parking accessibility and improve the overall traffic movement throughout the city. As traffic congestion declines, less time is wasted, expenses are lower, and the environment becomes healthier.

This paper evaluates the smart parking meter expansion in 2018. I study and analyze the effect on the local gains for businesses and residents when parking meters switch from normal to smart tech. The study aims to examine the disparity between the area with the expansion of SFpark in 2018 and the one without a smart parking meter at the block group level. I evaluate the causal impact of the smart parking meter on local business activities in San Francisco. The updated meter technology enhances the traffic experience for individuals, facilitating greater mobility for more people in congested areas. In a way, SFpark can positively increase people's productivity and local business activities. The primary outcome is the growth rate of the number of businesses. This measure hopes to analyze how the upgrade from normal to smart SFpark meters might attract more businesses to enter and stay in the market longer than other parts of San Francisco, where no meters exist. I expect any differences in the growth rate of the number of businesses between SFpark and non-SFpark block groups to be significantly driven by the introduction of SFpark itself.

In the analysis, any changes in demographic or economic outcomes, such as income levels or population, may be linked to improved urban amenities brought by SFpark technology. Improving mobility with better access to services and businesses can be viewed as an enhancement to urban amenities. When urban amenities improve, they can attract higher-income individuals and businesses, thereby influencing the demographic and economic characteristics of the area. Since each block group has a different ratio of meters to businesses, I also investigate how the effects might depend on the meter's density and the growth rate of the number of businesses.

My paper differs from previous studies in that I focus on the effect of the upgrade of parking meters on nearby businesses' behaviors. This is an important topic in urban planning to understand the efficiency of parking not only for traffic management but also for its impact on business operations. Furthermore, I illustrate the variations in effects based on the distribution of the meters in relation to the density of people and business stores.

I find that my results are related and contributed to the following literature. In mid-2014, SFMTA published a very detailed evaluation of the benefits of the SFpark pilot project. Key findings, such as transit performance, environment, and economic vitality, were emphasized in the pilot areas with 7,000 out of 28,000 smart parking meters. Additionally, sensors were placed in three control neighborhoods to provide baseline data for evaluation. SFMTA claims that the introduction of SFpark positively impacted the local business compared with other parts where SFpark has not been implemented yet. For example, sales tax revenues rose over 35% in SFpark areas compared to less than 20% in other parts of the city. From the evaluation, SFpark is argued to make it more "attractive" for drivers to visit restaurants, shopping malls, and other entertainment activities. The data suggests that the pilot area had a 30% increase in people who visited for shopping or dining compared to people who drove for other reasons, while the control area had no change. (SFMTA, 2014). SFpark intends to improve parking availability and enhance traffic flow. Their finding may suggest the positive impact of the smart parking meter on local business activities. As more people visit and shop in the SFpark region, more firms enter the market and open their stores.

The structure of the paper will be as follows. The data section outlines the data source for demographics, steps to obtain the meter density, and the number of business data through ArcGIS. The empirical strategy section presents how I designed the research and constructed the Difference in Difference regression estimator. I then expanded the model into the dynamic version to analyze the dynamic effect before and after the treatment period - 2018. Since the location of the meter is spatial data and is not randomly assigned, there is a possibility of spatial correlation. The paper describes spatial dependence and discusses how standard errors can be larger when accounted for by the spatial error model (Hsiang, 2010). In the heterogeneity with treatment intensity section, the results highlight that as the concentration of individuals or businesses per meter increases, the positive effects diminish or even decrease.

2 Data and Sample Construction

2.1 Data

In this section, I describe how I construct the analysis datasets. The sample relies primarily on two data sources. The first data source is from the city of San Francisco. The city published a map of SFMTA's parking meters and the businesses that pay taxes to the City and County of San Francisco. The second is American Community Survey (ACS) data from the U.S. Census Bureau, which contains census demographic data for each block group in San Francisco from 2013 - 2022. The block group unit is a division of census tracts and usually contains between 600 and 3000 people. In other words, census blocks are grouped into block groups, which are grouped into census tracts. The paper focuses on the block group-level data in San Francisco.

2.2 Sample Construction

The analysis is based on the 2010 Geographic Boundaries with 581 block groups in San Francisco. The geographic boundaries were redrawn in 2020, with 681 block groups in the city. Because ACS releases census data only for the new geographic boundary after 2019, I apply the block-group-to-block-group crosswalk file from the National Historical GIS to estimate the data from 2020 onward for the 2010 geographies. I use population-weighted measures to calculate the demographic data from the 681 bloc groups for the 581 block groups. For 2013 to 2022, each block group contains data on its population, personal income per capita (adjusted for inflation), unemployment rate, education attainment rate (bachelor or higher), and median age. I decided to drop three block groups because they do not have any data on population and income/capita data. Since the paper focused on the newly treated block group during the SFpark expansion in 2018, I decided to exclude the 54 block groups that already had a smart parking meter since 2011. I created panel data of 524 out of 581 block groups within 185 city census tracts from 2013 to 2022.

2.3 Parking Meter

Map of Parking Meters. - The dataset is published and updated by SFMTA. The Figure 1 lists the location and types of parking meters operating in the city. In the dataset, there are about 37,800 parking meters for various modes of transportation such as car, bike, motorcycle, and bus. For the purpose of the study, I only keep those meters under the SFpark programs, roughly about 28,200 on-street parking meters. With the information on the longitude and latitude of each meter, it is possible to extract what block group a meter is located on. I use ArcGIS with spatial analysis and intersection methods to count how many smart parking meters are in each census block group after 2018. (say about the figure below).

Map of Registered Business Locations. - The dataset is managed and published by the city of San Francisco. The Figure 2 shows about 333,000 businesses that paid taxes to San Franciso City. Nearly 262,000 are the unique number of businesses located inside San Francisco between 2013 and 2022, while the rest are outside of the city, but they still pay taxes to the city. In the dataset, I drop all businesses that are located outside. Each point on the map represents each business with detailed information on when the business enters and exits. I use ArcGIS to calculate the number of businesses entering and exiting each block group. The data also include the North American Industry Classification System by industry, which would be valuable for studying different effects of the SFpark program on various industries in San Francisco.

2.4 Construction of the Primary Outcome Variables

To understand the impact of smart parking on local business activity in San Francisco, the variable *stock* was calculated and chosen as the main component of the outcome. The panel dataset of registered businesses shows that each block group has the number of businesses entering and exiting by year. The baseline calculation for *stock* is thus:

$$stock_{it} = \sum_{2013}^{t} [enter_{it} - exit_{it}] \tag{1}$$

where $stock_{it}$ represents the total number of businesses that existed from the previous year and still operate at block group i at year t - from 2013 to 2022. The primary outcome of the paper is the rate of change of stock over the year.

$$pchange_{it} = 100 * \frac{(stock_{it} - stock_{it-1})}{stock_{it-1}} \tag{2}$$

where $pchange_{it}$ is the percentage change of stock of business or can be the growth rate of the number of businesses in the block group i in the year t from 2013 to 2022. In the analysis, I used the number of businesses in 2013 as the base year and focused on the block group with more than 35 businesses (5th percentile).

2.5 Descriptive Statistics

Table 1 describes summary statistics for 524 block groups from 2013 to 2022, with 5240 observations. The unemployment, education attainment, and growth rates are in percentage terms, and the other variables are recorded in units. Non-SFpark consists of 291 block groups with no smart parking meters, while the SFpark group has 233 block groups with an average of 74 meters. Although the average population and median age are quite similar between the two groups, SFpark block groups seem to have a higher proportion of people with bachelor's degrees or higher. This can relate to higher average income in SFpark block groups. *Table 1* also highlights that the average number of businesses in the SFpark area is nearly triple that in non-SFpark. The baseline differences may suggest that the SFpark block groups have relatively more advantages in terms of economic background. The density of businesses can be the reason that leads to the designation of meters as traffic is heavier and more parking management is needed. The key variable in this study is the growth rate of the number of businesses. It seems like the two groups have similar negative growth rates. However, since the average number of businesses in SFpark is much higher, the number of businesses that exited in terms of the units in SFpark can also be larger than the block groups without the smart parking meters.

3 Model and Empirical Strategy

3.1 Difference in Difference

Regarding the baseline measurement, I estimate the following two-way fixed effect model:

$$y_{gtc} = \delta_g + \tau_t + \beta(SFpark_g \cdot Post_t) + \epsilon_{gtc} \tag{3}$$

where the dependent variable, y_{gtc}, represents a **primary outcome** for block group g at year t and located inside the census tract c. This indication is a potential outcome of understanding the impact on the business environment since it analyzes the inflow and outflow number of businesses at a block group.

The independent variable is the interaction term *SFpark* multiplied by *Post*. It is an indicator variable equal to 1 only if the block group g is located in the SFpark expansion region and after a year $t \geq 2018$, as when San Francisco City upgraded normal to smart parking meters in 2018. The regression model also controls for δ_g as a block group- and τ_t as a time-fixed effect in a panel DiD setting. I estimate equation (3) using the Ordinary Least Square (OLS) methods and cluster the standard errors at the census tract level since there is a possibility for correlations across census block groups within tracts.

The coefficient of interest, β, is the average treatment effect on the growth rate of the treatment group after the expansion of the SFpark program. Specifically, β reflects the difference in the average rate of change of the number of businesses between the SFpark and non-SFpark block groups. To a certain extent, the impact on the growth rate on the number of businesses after the upgrade of smart parking meters is unclear as to whether β it should be positive or negative. If parking fee rates and traffic congestion remain high in intensive-demand areas where many businesses are located, β may be negative if visitors decide to go elsewhere to shop. This can hurt the existing business owners in the SFpark region because they need to take into account the peak time for smart parking meters. On the other hand, I expect β to be positive as drivers can experience better parking availability and traffic flow, allowing them to spend less time cruising and increase shopping time. Alternatively, local residents may decide to use public transportation or other travel modes, which indicates no significant effect on the local businesses' activity.

The empirical strategy framework to (3) is a standard panel Difference in Difference setup. Hence, the two following assumptions are essential to identify the treatment effect from analysis. Firstly, the growth of the number of businesses in either group has experienced and evolved along parallel trends before the treatment period. The growth of the number of businesses in treated and control block groups should react similarly to macro-economic conditions and other shocks before the expansion of the SFpark program. To ensure this assumption, I have created the plot for the average yearly growth rate trend before 2018. I also plot other block group economic and demographic characteristics to investigate if there are any external significance shocks. Secondly, the strategy assumes the average block-group-level treatment effects are homogeneous across the treated block groups in San Francisco City. This emphasizes that the designation of smart parking meters is assumed to be exogenous. Nevertheless, it is not necessarily true that the location of meters is random as they cluster together in certain parts of the city, and there is the possibility of spatial autocorrelation. The later part of the paper will address this issue with Moran's I test and spatial error model to address the preciseness of the estimation from the model (3).

Limitations and Remedies. - The model might not display the plausibility of the assumption of parallel trends. Additionally, the result from the model might not fully capture how long it takes and when the treatment impacts the growth of the number of businesses. I address this concern by estimating a fully dynamic version of equation (3) to check for potential pre-trends and understand what year the effect is greatest. In the later part of the paper, I address the model's reliability and whether the treatment effects are heterogeneous across groups with different treatment categories. The treatment effect might vary depending on the meter and business density within the SFpark block groups.

3.2 Dynamic Version

To test for similar trend assumptions and analyze the dynamic effect, I estimate an event-study version of the model (1) with the interaction term following the panel data DiD setting. This framework not only tests the assumption but also evaluates the treatment effects by years of expansion. The following equation is the estimation:

$$y_{gtc} = \delta_g + \tau_t + \sum_{k=-5}^{-2} pre_k \times SFpark_{k(gt)} + \sum_{h=0}^{4} post_h \times SFpark_{h(gt)} + \epsilon_{gtc} \tag{4}$$

where y_{gtc} is the outcome that I am interested in as above, and $SFpark_{(gt)}$ is a set of interactions equal to one only if the block group g is located in the SFpark expansion area for each year with 5 years before and 4 years after the treatment period, 2018. In other words, each year gap from the expansion year - 2018 - has a dummy indicator, and $SFpark_{(gt)}$ is a set of multiplication between the year dummy indicator to the treatment group - block groups in the SFpark area. As before, δ_g and τ_t are the census block group and time-fixed effects. When I estimated the model (4) using the OLS, I omitted the value of one year before upgrading to smart meters as the base year. The estimation is performed with standard errors clustered at the census tract level.

From the results, I look closely at the coefficients of the interaction from the model (4). By looking at the coefficient of the pre-trends, the assumption of parallel trends can be justified and studied to see if there are any other strange behaviors. The analysis primarily focuses on $post_0$ as the immediate impact, while $post_1$ and $post_2$ reveal the delay effects. These coefficients capture the relative impact of the expansion toward the growth rate to the base year. The statistically significant coefficients on event dummy variables reflect the significant impact throughout that period.

4.3 Spatial Dependence

One may worry about the spatial correlation among the census block groups with meters as their location are clustered. The research design above treats each observation as an independent assignment, and so does the error term. However, since I am working with spatial data, the unobservable variable of one block group can impact the error term of nearby block groups. A common test for spatial dependence is Moran's I, a statistical measure for spatial data. From there, the z-score statistic determines the necessity of the spatial error model, where only the error terms in the regression are correlated. For simplicity, let's suppose the following specification:

$$y_i = \beta x_i + \lambda w_i \epsilon_i + \mu_i \tag{5}$$

where μ_i represents the random error, independent identically distributed (i.i.d.) errors. λ is the coefficient of the spatially structured error. If there is no spatial correlation between errors, $\lambda = 0$, we can estimate the effect using the model (3). Otherwise, standard errors can be misleading, and the coefficient will be less efficient if $\lambda \neq 0$. In the analysis, I apply this method to model (3) to evaluate if there exists a correlation between the block groups.

4 Results

4.1 DiD results

The results of the Difference-in-Differences (DiD) regression highlight the comprehensive explanation of the impact of the SFpark program on local business activities - the growth rate of the number of businesses. From *Table 2*, the estimation β is 0.721% and is statistically significant at 10% levels, revealing the positive impact of upgrading the normal to the smart parking meter on the growth rate. This implies that if the block group has the smart parking meter, more businesses are entering relative to exit compared with the previous year. Additionally, I include the unemployment rate and per capita income level as time-varying covariances in the regression to account for their impact on the growth rate of a number of businesses. From *Table 2*, the estimation after including the covariant reflects a higher positive impact with 0.792% and is statistically significant at 5%. The slight increase in estimation indicates the presence of an omitted variable in the model (3). The per capita income significantly alters the estimation and may indicate the relationship between high-income regions and their growth rates. Since the average number of businesses is much higher in the SFpark region, the percentage change can reflect the much higher number of firms in absolute units entering the blocks relative to the non-SFpark region. The result is in the direction I would expect. As traffic patterns become more efficient, local businesses can improve their sales as shopping becomes more convenient. Areas equipped with SFpark attract greater investment, leading to the opening of more businesses on streets with smart parking meters.

To test for the parallel trend, I plot other demographics such as income per capita Figure 5, population Figure 7, education attainment rate Figure 9, median age Figure 8, and unemployment rate Figure 6. The graphs suggest that the evolution of the population, education attainment rate, and unemployment rate is non-statistically significant after the treatment period. This implies that the upgrade of SFpark has no or little impact on these outcomes and thus can be included in the model as a time-varying covariant.

Nevertheless, the effect on the level of income per capita is positive and significant from 2020 onward. The estimation can be related to the exogenous shock of Covid 19, and most people received the stimulus check from the government. The extra cash during COVID-19 significantly increased the income level between the two groups, which might not be due to the expansion of the SFpark program in 2018. If this is the case, the level of income per capita can be a covariant variable in the estimation. Another reason is that reduced congestion and better mobility might indirectly affect residential amenities, potentially making neighborhoods with SFpark meters more attractive for higher-income individuals. In other words, the migration pattern might lead to higher income in the SFpark region but is not directly related to the impact of the smart upgrade of the parking meter.

4.2 Event DiD results

The results from *Table 3* illustrate the treatment effects by years rather than average treatment effects. The model also reveals evidence for parallel trends from the outcome of $pre_{-}4$ to pre_2. Since their estimation is not statistically significantly different from the omitted base year, the assumption of a parallel trend can be supported Figure 4. Furthermore, I plot other demographic data to verify that there is little to no significant change in the population, education attainment rate, and median age. The plot for the unemployment rate and level of income per capita notes the shock of COVID-19 as both went up significantly.

I am interested in the estimation for $post_0$ to $post_4$ as it explains the lag effects of the SFpark program on the growth rate. $post_0$ is reflects the immediate effect with about 1.458%, while the rest is the delay effect 1 to 4 years after the treatment period 2018. Notably, the trend of effects somewhat reflects the existence of Covid-19. $post_2$ is negative and also statistically significant, with a 1.432% lower growth rate. To a certain extent, this result emphasizes that SFpark had worsened the growth rate during but not entirely due to the hit of the pandemic in 2020. $post_3$ and $post_4$ reflect the impact of SFpark on the local businesses' activities during the recovery period. The estimation for $post_4$, the year 2022, shows that the SFpark region has a 1.237% significantly higher growth rate than non-SFpark. The results from *Table 3* can somewhat highlight the benefits of smart parking meters after COVID-19 as more businesses enter relative to exit in the block group with SFpark programs.

4.3 Spatial Correlation - Preliminary Results

The results from Moran's I test suggest I can reject the null hypothesis that there is zero spatial autocorrelation present in the growth rate between the block groups in San Francisco. From ArcGIS, I use the centroid of block groups to determine the distance of each observation. The distance from one to another ranges from 200m to 1km. Although the results from *Table 6* are similar at 0.79%, it is less precise in the spatial error model as standard errors increase. In the spatial data, the unobservable factor of one unit can affect the errors of other nearby units, which inflate the residuals. As I increase the distance cut off, the standard error becomes larger.

In the future, I will look more into the spillover effects as more businesses entering one block group can raise the market competition within and neighboring block groups. Thereby, the effect of one block group can increase (lower) the activities of businesses in the neighbor block groups. I will also investigate the spatial lag model concerning the independent variable, which is the SFpark expansion. It would be intriguing to examine the impact of smart parking meters not only within the block group but also in adjacent block groups.

The preliminary results of *Table 7* follow the Spatial Auto-regressive fixed-effects model: the direct effect is 0.805% and significant; the spill-over effect is -0.076% and non-significant. The total effect is 0.728% and significant at the level of 10%. The negative spillover effect might indicate that business entry in one block group causes the exit in nearby block groups. This can be due to the concentration of the market as people tend to start their businesses in certain areas rather than spread out other places. However, as the result is minimal and insignificant, spillover might not happen.

5 Heterogeneity by Intensity of Treatment

From *Table 4* The number of smart parking meters at the block group level is skewed on the lower side. To ensure an equal split of the treatment group, I separated the treatment group by quartile into the following thresholds: low, medium, high, and extreme on different variables such as the meter density, number of people, and businesses per meter.

The preliminary results of *Table 5* suggest that the treatment effect decreases as the block group has more people or businesses per smart parking meter. This is similar to my hypothesis that if the block group is too crowded, the benefit of having smart parking meters on the growth rate diminishes. On the other hand, the block group that falls into the medium and high categories in terms of the number of businesses per meter has the highest effect compared with the other two categories. The Figure 10 suggests the overcrowding of businesses and individuals can cause congestion, even if there are smart parking meters. In the extreme block group, the traffic flow might be similar to the block group without the meter. Hence, the effect is minimal and not statistically significant.

6 Discussion and Conclusion

In this paper, I explore the impact of smart parking meters on the local economic activities of businesses and residents in San Francisco. The key finding reveals the positive effect of the upgraded meter on the growth rate of the number of businesses. The region with the SFpark program increases the growth rate by 0.75% on average compared with other block groups without the smart parking meter. The estimation suggests that the traffic flow is an important factor in the productivity of firm operations and the urban amenities. Although no one likes to pay for parking, parking meters are crucial for enhancing parking availability and minimizing congestion in city environments.

In urban planning, the density of people and the number of businesses are leading causes of traffic congestion. The heterogeneity results emphasize that the effect of smart parking meters lessens in the block groups with very high amounts of residents and stores per meter. The effect of SFpark on moderate areas is about 1.2% compared with 0.05% in extremely congested areas. Even though SFpark was designed to improve the traffic flow, the overcrowding effect can outweigh the benefits of smart parking meters. Even if there is a smart parking meter, extremely dense areas such as downtown continue to face the same traffic congestion as other areas without smart parking meters. In future work, I intend to show the impact could vary based on the block groups and the kinds of businesses present. I expect that smart parking meters will have minimal effect in the financial district but might have a greater effect on block groups with a higher concentration of retail establishments like shops, cafes, or dining venues.

The paper's statistical model for estimating the effect relies on several simplifying assumptions, such as treating each observation as independent of the other. Since the topic is related to spatial analysis, the variation of unobservable factors between block groups can cause less precise estimation. I address this issue with the spatial dependence test with error and lag models. Even though the standard error becomes higher for spatial analysis, I find that the estimation translates to a causal impact on the growth rate of the number of firms. I am working on the spatial lag model to understand the pattern of the spatial relationship between block groups and identify if there is a spillover effect of the SFpark expansion in 2018. Even though the growth rate of businesses enables straightforward comparisons, the results may not entirely indicate the performance of an individual business, such as its sales revenues. It would be interesting to study the impact of smart parking meters on business revenue at the block group or tract level.

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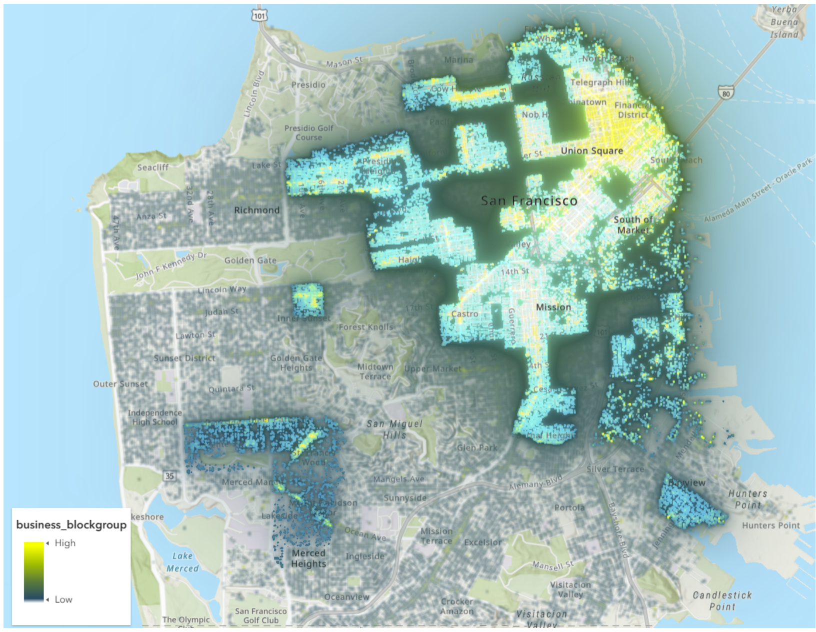
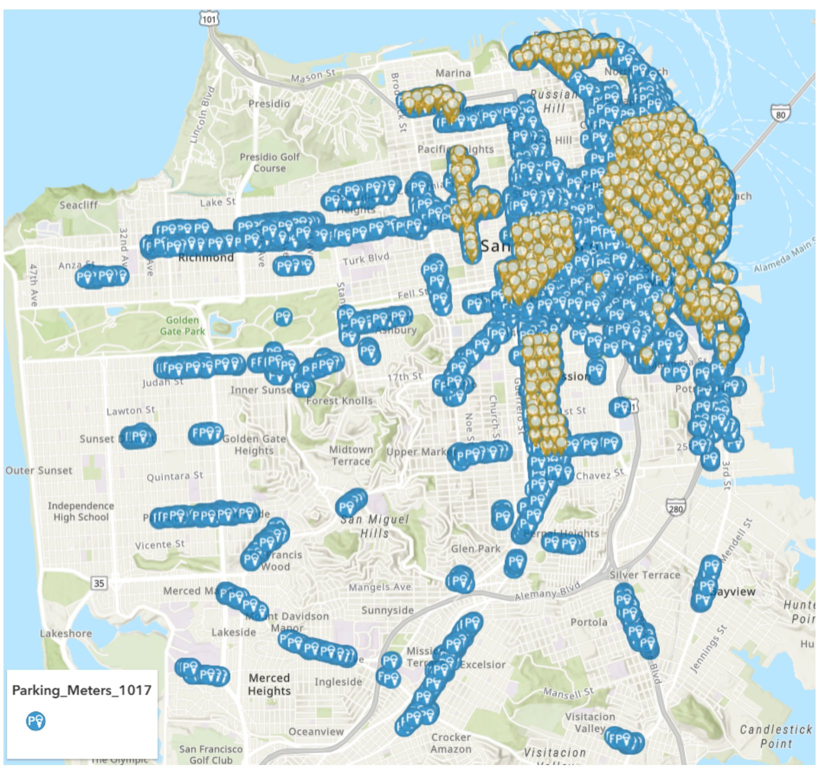
Figure 1: Map of Registered Businesses



Note: A heat map illustrates the business density. From the figure, the majority of businesses are opened and closed in the northeast part of San Francisco.

Figure 2: Map of Parking Meter

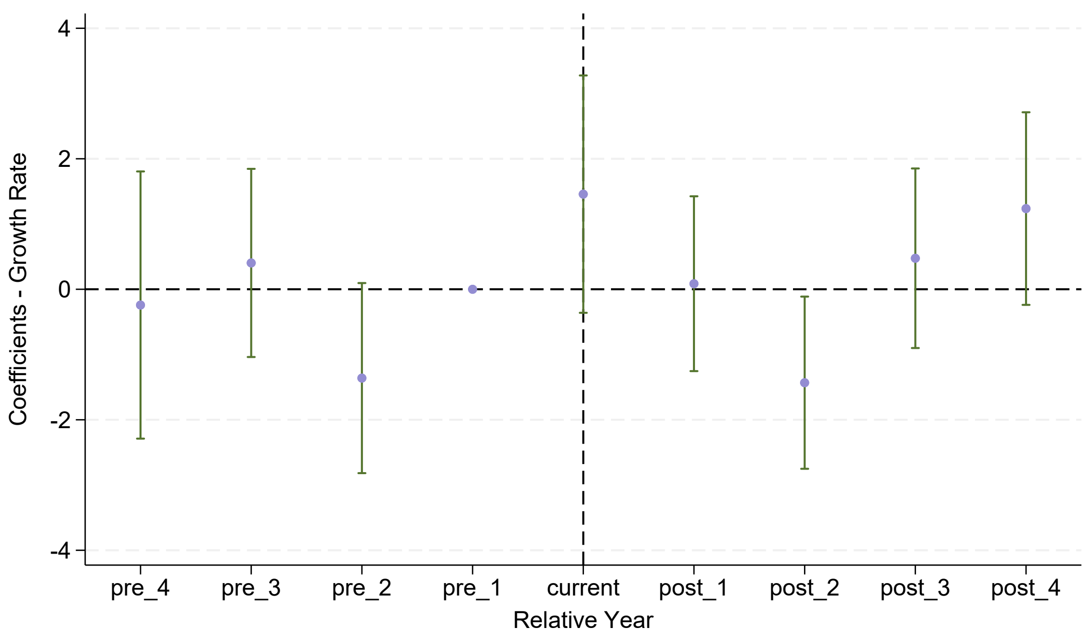


Note: Each blue dot represents one parking meter in San Francisco city. The Yellow dot displays the region of the pilot meter that was already upgraded in 2011. This paper focuses only on the newly treated during the expansion in 2018 - blue dots.

Figure 3: Evolution of Growth Rate on Number of Businesses

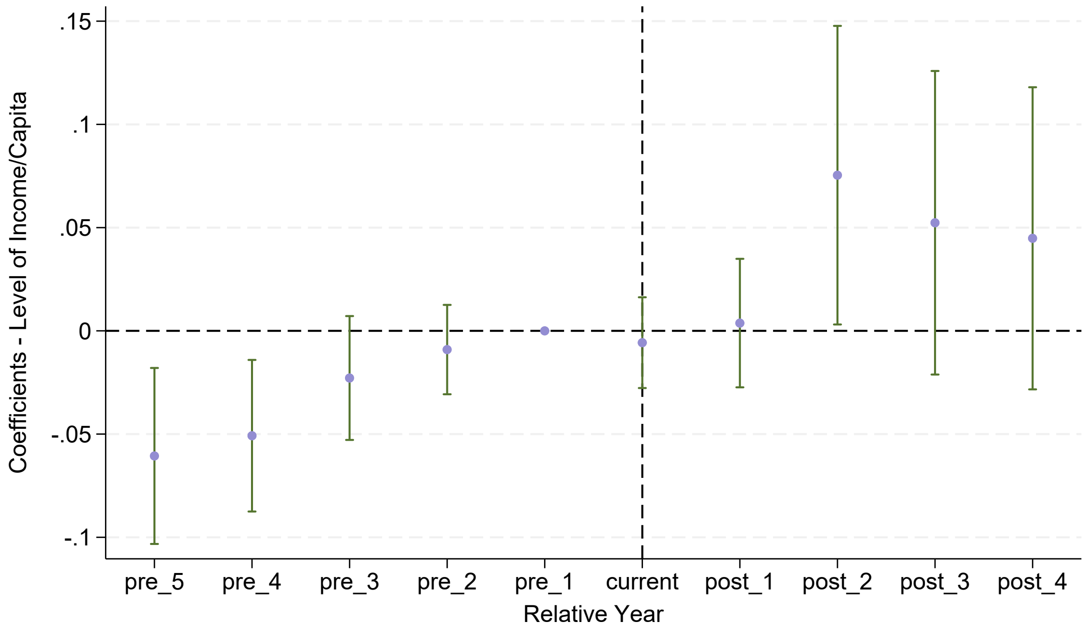
Note: The graph illustrates the average changing rate in the number of businesses each year from 2013 to 2022.

Figure 4: The effect of SFpark on Growth Rate on Number of Businesses



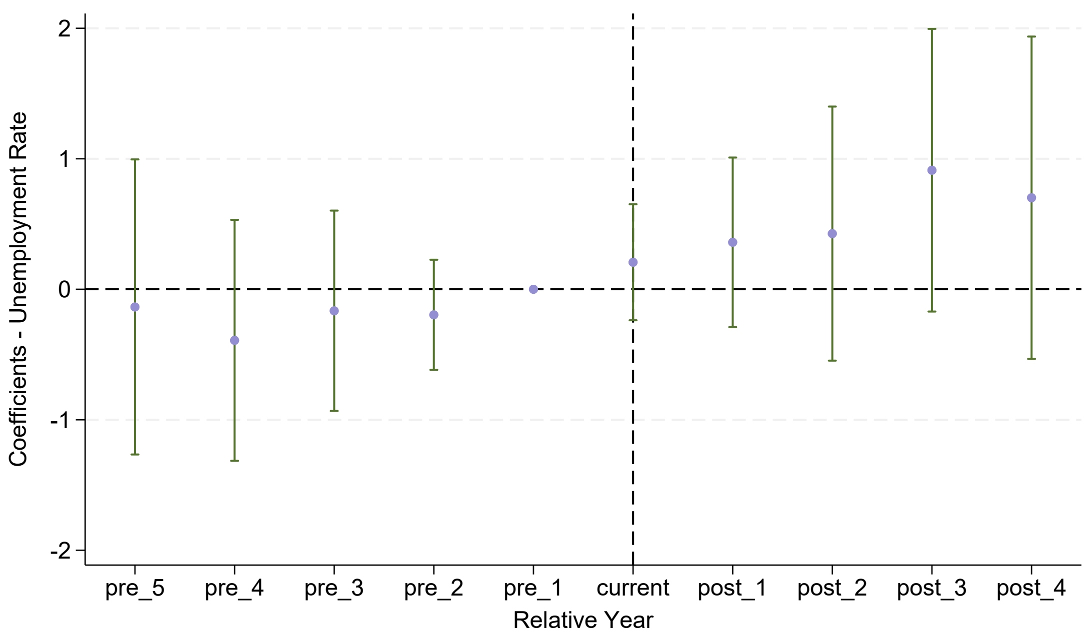
Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 5: The effect of SFpark on Level of Income/capita



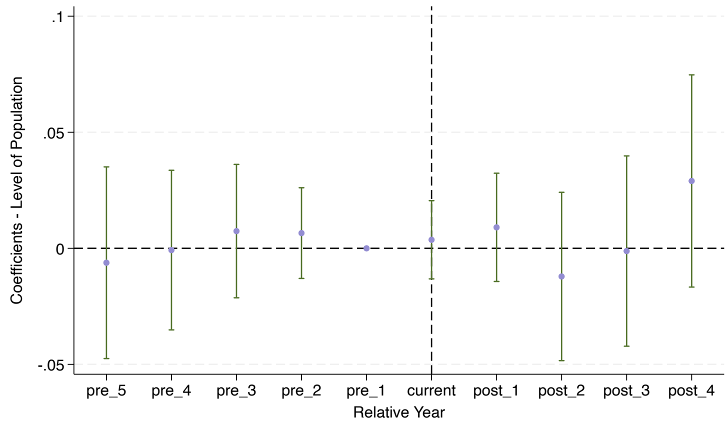
Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 6: The effect of SFpark on Unemployment Rate



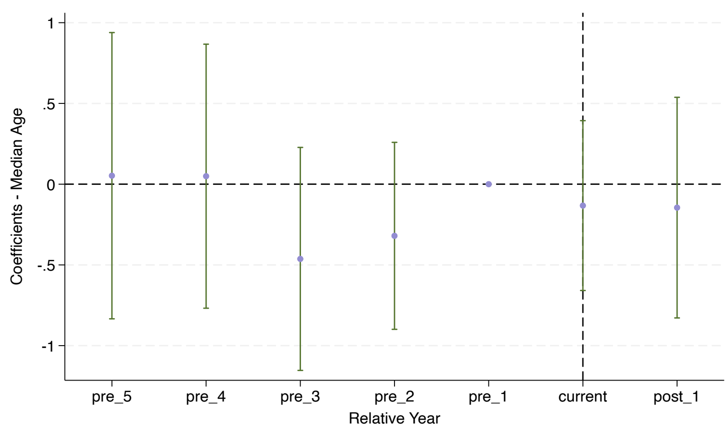
Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 7: The effect of SFpark on Level of Population



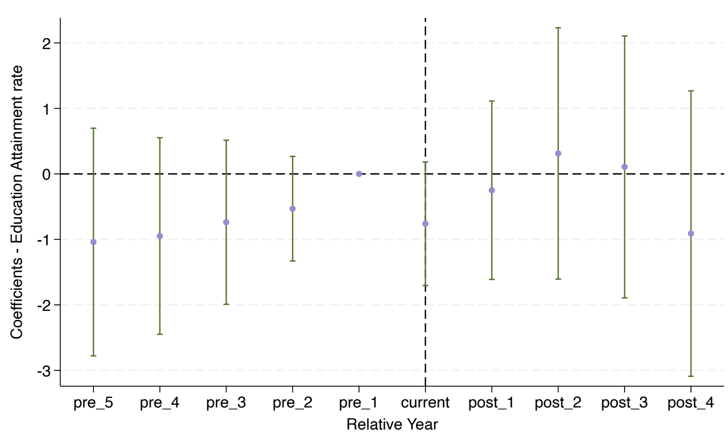
Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 8: The effect of SFpark on Median Age



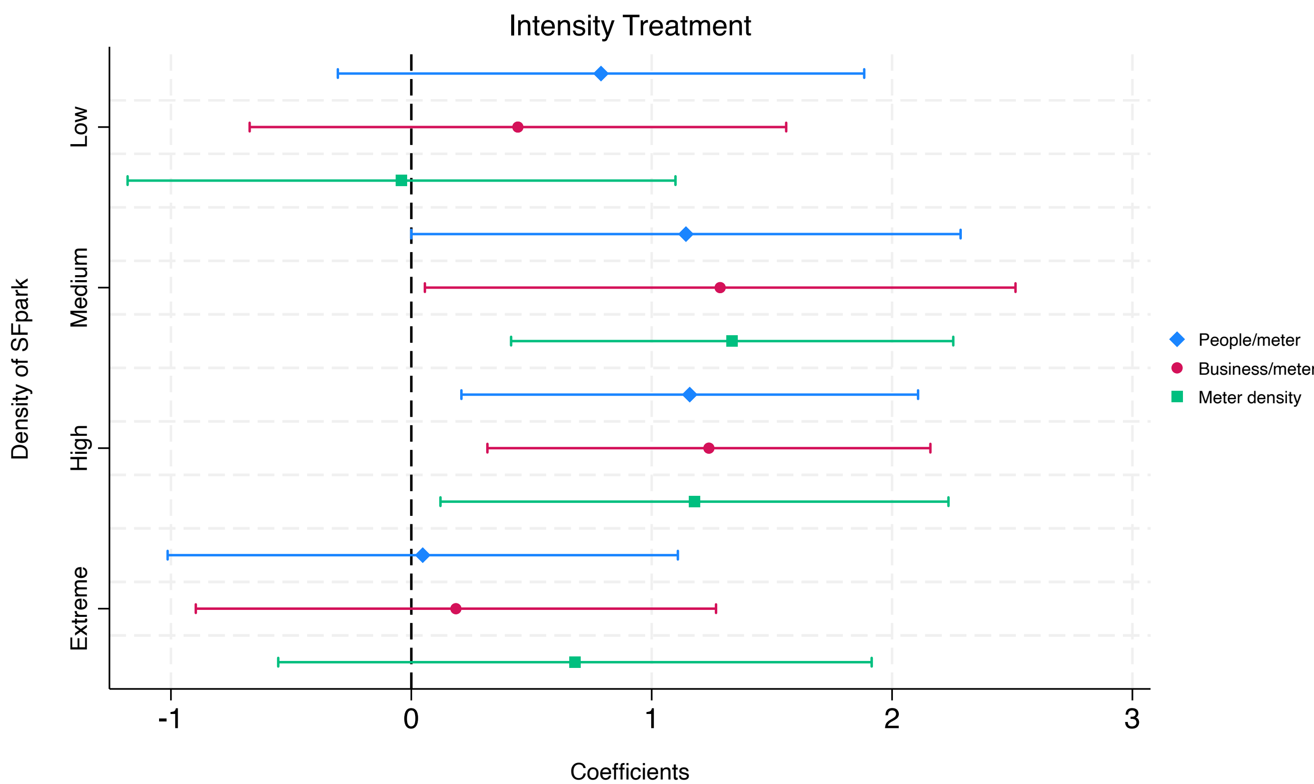
Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 9: The effect of SFpark on Education Rate



Note: In this graph, the pre-1 year serves as the base year and is omitted from the model. Current represents the year 2018, when the treatment period begins.

Figure 10: Intensity Treatment and Growth Rate on Number of Businesses



Note: In this graph, the graph compares the differences in effect within the treatment group. As the density moves from low to high, the effects are lessening. The description for density categories is displayed in Table 4. It seems like the High and Medium categories have the strongest effect and are statistically significant.

Table 1. Descriptive statistics

Variable	Non-SFpark	SFpark	Total
N	2,910 (50.3%)	2,330 (44.5%)	5,240 (100.0%)
Year	2,017.500 (2.873)	2,017.500 (2.873)	2,017.500 (2.873)
Median age	41.986 (9.306)	42.230 (13.654)	42.094 (11.445)
Population	1,425.002 (570.721)	1,474.980 (642.415)	1,447.225 (604.104)
Income/capita	65,919.929 (40,895.037)	68,778.940 (42,373.268)	67,191.207 (41,579.121)
Meter density	0.000 (0.000)	74.378 (86.894)	33.073 (68.723)
Growth rate	-0.513 (9.816)	-0.531 (9.606)	-0.509 (9.475)
Unemployment rate	5.889 (5.358)	5.734 (5.380)	5.903 (5.453)
Education attainment rate	55.422 (22.096)	57.336 (21.536)	56.273 (21.868)
Number of businesses	90.166 (57.275)	211.082 (164.479)	143.932 (132.133)

Note: Sample defined between 2013 and 2022 to 524 block groups in San Francisco city. The standard deviation is inside the parentheses. The table illustrates the summary for block groups with and without the smart parking meter under the SFpark program. "Education attainment rate" is the share of the population that earned a bachelor's degree or higher. Growth rate, unemployment rate, and education attainment rate are displayed in percentage values.

Table 2: DiD Regression Results – Model 3

	(1)	(2)	(3)
VARIABLES	Growth rate	Growth rate	Growth rate
DiD	0.721*	0.775*	0.792**
	(0.410)	(0.409)	(0.398)
Observations	4,653	4,653	4,653
R-squared	0.384	0.399	0.399
Number of Block Groups	517	517	517
Covariates	None	Inc & Unemploy	All

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Standard error adjusted for 185 clusters in number of census tracts in San Francisco city. "Inc" stands for income per capita. "Unemploy" is the unemployment rate variable. "All" includes level of population, income/capita, unemployment rate, and education attainment rate.

Table 3: Event Study Regression Results – Model 4

VARIABLES	(1) Growth rate	(2) Growth rate
pre_4	-0.242	-0.279
	(1.038)	(1.048)
pre_3	0.404	0.387
	(0.731)	(0.731)
pre_2	-1.361*	-1.368*
	(0.738)	(0.739)
current	1.458	1.452
	(0.922)	(0.920)
post_1	0.0856	0.0849
	(0.679)	(0.679)
post_2	-1.432**	-1.375**
	(0.669)	(0.666)
post_3	0.476	0.514
	(0.698)	(0.692)
post_4	1.237*	1.268*
	(0.748)	(0.742)
Observations	4,653	4,653
R-squared	0.402	0.403
Number of block groups	517	517
Control	None	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Standard error adjusted for 185 clusters in the number of census tracts in San Francisco city. “All” includes the population level, income/capita, unemployment rate, and education attainment rate. “Pre_1” is omitted as the base year.

Table 4: Quartile Summary for Intensity Treatment

Variables	Min	P25	P50	P75	Max	N
Number of Meters	1	26	57	114	1144	2330
People per Meter	.9583	11.4658	23.139	51.12	1398	2330
Business per Meter	.4082	1.935	3.28	5.789	78	2330

Note: Data for population and number of businesses are based on the year 2013. The number of meters is the same throughout the period.

Table 5: DiD Regression Results for Intensity Treatment

VARIABLES	(Number of people / meter) Growth rate	(Number of businesses / meter) Growth rate	(Number meter) Growth rate
Low	0.789	0.443	-0.0407
	(0.555)	(0.566)	(0.578)
Medium	1.143*	1.285**	1.335***
	(0.579)	(0.623)	(0.466)
High	1.158**	1.238***	1.178**
	(0.482)	(0.467)	(0.536)
Extreme	0.0475	0.186	0.681
	(0.538)	(0.549)	(0.626)
Observations	4,653	4,653	4,653
R-squared	0.399	0.399	0.399
Number of block groups	517	517	517

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Standard error adjusted for 185 clusters in the number of census tracts in San Francisco city. The treatment group is divided by quartile according to the population and number of businesses in 2013. “Low” is below or equal 25th. “Medium” is between 25th - 50th. “High” is 50th - 75th. “Extreme” is above at 75th.

Table 6: Spatial Regression Results

VARIABLES	(1) OLS	(2) Spatial	(3) SpatHAC
DiD	0.722**	0.722	0.722*
	(0.401)	(0.503)	(0.477)
Observations	4,653	4,653	4,653
R-squared	0.001	0.001	0.001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The regression is use a linear bartlett window for spatial correlations, instead of a uniform kernal cutoff.

Table 7: DiD regression with Spatial Matrix data.

VARIABLES	(1) Direct	(2) Indirect	(3) Total
DiD	0.805**	-0.076	0.728*
	(0.409)	(0.048)	(0.374)
Observations	4,653	4,653	4,653
Number of groups	517	517	517

Note: Direct effects are the effects of the block groups on itself. Indirect effects are the effects one block groups have on others, also known as spillover effects.